PARKING CAPACITY IMPLEMENTATION EVALUATION TOOL

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Abstract: This paper presents a novel tool for optimising residential parking allocation in urban environments using linear programming techniques. The tool addresses the growing challenge of parking space management in cities by quantifying parking utilisation and accessibility. It employs a unique application of the transport problem from Graph Theory to allocate parking supply to household demand while considering real-world constraints such as walking distances and infrastructure limitations. The methodology involves the pre-processing of supply, demand, and distance matrix data, followed by an optimization process that minimises total walking distance and penalises unmet demand. The tool's effectiveness is demonstrated through an experiment in the Czech town of Slaný, showcasing its ability to evaluate current parking situations and assess the impact of potential changes in parking supply. Key outputs include the percentage of satisfied demand, utilization rates of parking supply, and detailed allocation maps. This approach provides urban planners and policymakers with valuable insights for developing efficient and sustainable parking solutions, while also highlighting areas for further research in data preparation and model refinement.

Key words: *capacity, evaluation, GIS, graphs theory, linear programming, parking, parking allocation optimization, shortest path, transport problem, walking distance*

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1. Introduction

Parking has progressively become a full-scale problem across countries and municipalities of different sizes [25]. The estimate is that there are now more than 1 billion passenger cars in the world [10, 23], many of them employed in cities [10]. Some analysts say Western Europe contains 300 million parking places [22], while estimates suggest the US boasts two billion [13]. Often, that real estate is centrally located and very valuable. Just a single standard parking space, which measures a little more than 6×3 m, takes up approximately as much space as a small Parisian studio apartment, a low-income housing unit in India, or three office

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cubicles [23]. Austria, despite the fact that automobile use accounts for only 47% of the mode share, this mode takes up 92% of the urban space used for stationary traffic. Meanwhile, cyclists and pedestrians account for 33% of the mode share but only receive 5% of the urban space for stationary traffic (benches, cycle racks, and so on) [10]. In Canada, a typical automobile is parked 23 hours each day and uses several parking spaces each week. Parking facilities are an essential component of a transportation system. They are also costly; for every dollar motorists spend on their vehicles, somebody (they, their employers, local government, businesses, etc.) spends around a dollar to park it [21]. Parking conflicts are among the most common problems facing public officials. Such problems are often defined as inadequate supply (too few spaces are available), but they can also be defined as inefficient management (available facilities are used inefficiently). Management solutions tend to provide better outcomes than simply expanding supply [21].

In the Czech Republic, the issue has risen, in importance and prevalence, due to the increasing number of motor and personal vehicles. Between the years 2016 and 2021, the number of personal cars normalized to the number of citizens has increased by 18%, and the overall number of motor vehicles per capita has increased by 17%. Across various cities, the number of personal cars has increased by between 12 and 19 percent between the years 2016 and 2021 (5 years). When we evaluate a 10-year look-back period, the increase in personal cars per capita is between 32-38% equating to more than a third more [24]. Cities cannot and should not grow healthily at these alarming rates [35]. However, this growth of demand from the sheer and ever-increasing number of cars in cities creates pressure on municipal leaders to do something about this situation. Resources are often limited, and deciding where and if additional parking capacities should be brought about can be challenging.

The consistent and continuous increase in the global population is creating many challenges for policymakers in areas of life such as housing [2, 9], education and higher education [31, 18], health [12, 5], and transportation [7]. The demand for transportation in general and for private ownership of vehicles in particular is leading to growing traffic congestion [3], slower traffic speed, and hence reduced work hours and lower work productivity [34], increasing air pollution [20], a rising number of traffic accidents [4], and so on. This state of affairs exists in many countries, but it is particularly conspicuous in countries characterized by a consistent increase in the local population, such as Israel [36]. A necessary perspective is finances – in the city centre of Prague, the cost of building one underground parking space is up to CZK 2 million (EUR 80,000) [16]. Parking is a significant cost for the company. Building a parking lot at every destination is expensive, inefficient, and sometimes impossible. Parking lot construction also has a major impact on city life [35]. The construction of a parking space typically costs an investor hundreds of thousands of crowns. In the case of larger cities and the construction of underground parking, the cost rises to millions. The cost of one parking space in our calculations today comes out to about CZK 1.5 million (EUR 60,000). The high construction costs associated with building them in turn make the construction of an apartment building more expensive. A proposed new regulation would affect all municipalities and towns except Prague, Brno, and Ostrava, which are governed by their own building regulations [27, 26].

While the figures mentioned above give a basic idea of cost, it is important to note that specific areas may require higher terrain/grade adjustments and can thus cost substantially more. This all in addition to the reality that in many cases the municipality would need to buy the property. There are; however, a number of additional factors that can be, at times, difficult to quantify. The most important perspective is the benefit or total utility of realised new parking capacities.

Currently, Prague is discussing the Concept of the system of P+R (Park and Ride) parking garages, the operation of which is of fundamental importance to the solution of target car traffic in Prague. The car parks are intended mainly for the solution of external solo car traffic in relation to Prague. The system of P+R car parks currently has 19 car parks (16 locations) with a total construction capacity of 3,433 parking spaces. There are 2,652 parking spaces per 1,000 inhabitants of the city. The progress of the construction of P+R sites is in a deep deficit compared to the requirement set out tentatively for 2010 in the current master plan – about 3 thousand parking spaces achieved versus the original ambition of 12-14 thousand parking spaces, or a moonshot of up to 19 thousand parking spaces. In total, Prague has so far fulfilled its own principles for the development of the P+R system by only about one quarter. The key document for the development of P+R parking garages is the zoning plan and any changes to it that will enable their construction [15].

It is established, that new parking capacities are major investments, often discussed and planned over many years in advance of breaking ground. The financial costs play a major role, but how do we determine the benefit of new parking capacities? This paper offers a unique tool that can quantify and compare the overall availability of residential parking and changes based on additional capacity. It can, in short, calculate how many residents or any other type of specific users have a parking space within desired walking distance, and therefore quantify, how big of an impact a specific placement of new capacity can have. This tool can be used to quantify the current situation and compare various scenarios (difference placement of large parking garages, comparing the benefit of new parking capacities, etc.). The tool does more that just determine how much parking capacity is available within specific walking distance, it simulates human behaviour and optimises the distribution of parking spaces to the residents (or users, or vehices). Ultimately, it allows us to compare various scenarios of parking development and the demand coverage.

2. Research Question

The main research question then is "Can we quantify and compare the utilization of parking spaces and new capacities using spatial analysis?" The proposed tool utilises graph theory's transport problem task using linear programming in Python. This is a unique way of using this minimization task, that is normally used for servicing an area from depots or storage facilities or distribution centers. The transportation problem, primarily used in logistics and supply chain management, focuses on minimizing the costs associated with transporting goods from multiple origins to various destinations [37]. Here, we examine several key use cases that illustrate its typical applications and emphasize that it has not been traditionally utilized for the creation of origin-destination (OD) matrices in traffic forecasting.

Optimization of the Distribution of Oil Products This application involves optimizing the distribution of oil products to minimize transportation costs and improve efficiency. The model considers various supply and demand points and the associated transportation costs between these points, demonstrating the transportation problem's utility in resource-heavy industries such as oil and gas [1].

Minimization of Raw Material Costs in Iron and Steel Plants In the iron and steel industry, the transportation problem is employed to optimize the sourcing and distribution of raw materials from suppliers to manufacturing plants. This approach ensures minimal costs while meeting production requirements, highlighting its critical role in industrial logistics [30].

Optimization of Consumer Goods Distribution in Nigeria A case study involving Unilever Nigeria Plc focuses on optimizing the distribution of consumer goods in the South-East region of Nigeria. The goal was to minimize distribution costs while meeting demand across multiple locations, illustrating the transportation problem's effectiveness in improving supply chain efficiency [8].

Multi-modal Transport Optimization of Chemical Cargo This empirical study examined the transport of chemical cargo from Java to various destinations in Java and Sumatra. The study optimizes multi-modal transport—selecting the most cost-effective combination of transportation modes (e.g., road, sea) to meet delivery requirements efficiently [11].

New Algorithms for Transportation Cost Minimization Research in this area explores the development of new algorithms to enhance the efficiency of solving transportation problems. These methods, including modifications to traditional algorithms like the North-West Corner and Least Cost methods, focus on reducing overall transportation costs in logistics networks [29].

Solving Multi-Product Transportation Problems This study addresses the complexity of transporting multiple products with varying supply and demand constraints. It emphasizes optimizing the transportation of different goods simultaneously to minimize total transportation costs, thereby illustrating the transportation problem's adaptability in handling diverse logistical challenges [17].

Comparative Analysis of Mixed Transportation Problems A case study of the Ghana Bauxite Company Limited compares standard transportation problem formulations with mixed constraint scenarios. The goal is to determine the most cost-effective transportation strategy under varying constraints, demonstrating the problem's application in complex industrial logistics scenarios [19].

General Studies on Transportation Problem Optimization General studies in this domain explore various optimization techniques, including linear programming and heuristic methods, to solve transportation problems more efficiently. These studies aim to refine traditional approaches for better cost-efficiency in logistics, without addressing OD matrix creation for traffic forecasting [14].

Research Gap The transportation problem is a versatile tool primarily applied in logistics and supply chain management to minimize transportation costs across various networks. Its applications span over consumer goods distribution, multimodal transport optimization, and resource allocation in industrial settings. However, it has not been traditionally employed in the context of simulating human behaviour regarding the free will associated with getting to work or home on time. Meeting the demands from households and individuals through the supply of parking capacity is only one aspect of this very human problem. This is a novel approach that supports how flexible the Transport Problem can be.

The following chapters detail how this tool was used on real-life data examples followed by a complete methodology including the algorithm that the Python code was built upon. Results from this experiment are then shown and described.

3. Data

There are three main data inputs, as made obvious by the algorithm (Section 4.4):

- Demand data
- Supply data
- Distance matrix

The tool demonstrated in this paper expects all data in a CSV format. Below is a description of the structure and creation of all of these data with simplified descriptions of the methods of creation, since this paper focuses mainly on the computational tool (code), and not on data preparation.

Since the tool uses Graph Theory's transport problem, specific terminology is used to describe specific data:

- Demand data: cars of residents at the place of the specific residents' home;
- Supply data: available parking capacity represented at parking lot's centroid;
- Distance matrix: shortest path on real-life infrastructure (here the "cost" is equal to the distance traveled).

While in the preprocessing phase and working with GIS (Geographic Information System), the supply/demand data need to be represented geometrically as points (also for the distance matrix calculation). For the computation using the tool presented in this paper, the data need to have no geometry.

3.1 Demand Data

The demand data are, as stated, the residents, recalculated to the cars owned by the residents. For example, an apartment building might have 200 residents, but based on the number of private cars in the city in relation to the number of capita, it might be 100 or more cars for that apartment building. The cars are still located at the address of the resident because that is where the resident lives and they, in rational cases, want to park as close to their home as possible.

Structure of the Data:

- CSV File: Delimited by comma ",".
- ID: Unique identifier that starts at number 1 and continues without skipping any numbers or duplication until "n", where "n" represents the maximum number of populated or used address points.
- Demand: A whole number representing the number of cars that need to be parked assigned to the specific address.

The generation of the demand data might be more difficult whereas such data is not available in the Czech Republic. The only available relevant data is the number of citizens from the household survey (state-wide census) from 2021 [6]. Additionally, there is data about the total number of private cars in the state vehicle registry [24]. A simple distribution was used for the purpose of testing this tool, but it can be improved upon. The simple code, presented in Algorithm 1, is specific to the QGIS field calculator. Hence, the probability function is simulated by using random number generation.

3.2 Supply Data

The supply data required the least adjustment for the Town of Slaný, since it was readily available. Currently, there is no automated way to generate this data reliably. The municipality needs to have this data available to apply it. The only preprocessing involved with the existing data was filtering and centroid generation (and of course column reductions etc.).

The structure of the data:

- CSV File: Delimited by comma ",".
- ID: Unique identifier that starts at number 1 and continues without skipping any numbers or duplication until "n", where "n" represents the maximum number of populated or used address points.
- Supply: A whole number representing the number of public, legal parking spaces.

Algorithm 1 Vehicle assignment algorithm based on household residents.

Input: Number of residents in a household (denoted as `residents`).
Output: Number of vehicles assigned to the household.
Initialization: Set the number of vehicles to 0.

```
if residents = 0 then
  Assign 0 vehicles. {No cars if no residents.}
else if residents = 1 then
  Generate a random number between 0 and 100.
  if random number > 50 then
    Assign 1 vehicle. {50% probability of assigning a vehicle.}
  else
    Assign 0 vehicles.
  end if
else if residents = 2 then
  Generate a random number between 0 and 100.
  if random number > 25 then
    Assign either 1 or 2 vehicles (randomly selected). {75% probability of assigning
    a vehicle.}
  else
    Assign 0 vehicles.
  end if
else
  Assign floor(residents * 0.54) vehicles. {Apply 54% probability for the rest.}
end if
```

Return: Number of vehicles assigned to the household.

3.3 Distance Matrix

The distance matrix is vulnerable to the quality of infrastructure data. It can also be influenced by the chosen tool to calculate the shortest path. While Dijkstra was used to calculate the shortest path using QNEAT3 in QGIS, other tools can be used, such as the A* algorithm, etc.

The structure of the data:

- CSV file: Delimited by comma ",".
- demand_ID: Origin ID (household);
- supply_ID: Destination ID (parking lot centroid);
- Cost: Calculation of the cost based on specific settings of the algorithm (Typically walking distance, but it is also possible to use time or calories burned).

The distance matrix calculation is the most intensive calculation in the procedure, as it takes the most time. Based on the city, it can take from over one hour up to over 10 or more hours. This is also heavily influenced by the chosen algorithm and the power of the computer.

4. Method

This chapter presents a novel tool designed to optimise parking allocation in urban environments. The tool employs linear programming techniques to quantify parking utilisation while adhering to real-world constraints such as walking distance and infrastructure limitations. The basic construction of this tool utilises the concept of transport problem from the Graph Theory, exploiting the concept and its outcomes in an unforeseen way.

4.1 Data Requirements and Preprocessing

The tool requires three primary inputs:

1. Supply Data: Locations and capacities of parking lots (centroids).
2. Demand Data: Locations and parking requirements of households (address points).
3. Distance Matrix: Shortest-path distances between all supply-demand pairs.

The distance matrix is computed using Dijkstra's Algorithm on a detailed urban street network, ensuring that the model accounts for actual walking routes rather than straight line distances. The precision of this infrastructure data significantly influences the resultsing accuracy. A detailed description of the data and its structure is in Section 3. The tool that is described in this paper does not include the process of creating the distance matrix and assumes this input already exists.

4.2 Problem Formulation

Let $\mathcal{S}$ represent the set of parking supply points and $\mathcal{D}$ represent the set of household demand points. The primary decision variables are:

- x_{ij}: Parking capacity from supply point $i \in \mathcal{S}$ allocated to demand point $j \in \mathcal{D}$;
- y_j: Unmet demand for household $j \in \mathcal{D}$;

The objective function in Eq. (1) minimizes total walking distance and penalizes unmet demand:

$$\text{minimize} \quad \sum_{i \in \mathcal{S}} \sum_{j \in \mathcal{D}} c_{ij} x_{ij} + P \sum_{j \in \mathcal{D}} y_j, \tag{1}$$

where c_{ij} is the walking distance between parking lot i and household j, and P is a large penalty coefficient for unmet demand.

4.3 Constraints

Set of constrains were formulated in Eqs. (2)–(6).

1. Supply capacity:

$$\sum_{j \in \mathcal{D}} x_{ij} \leq s_i \quad \forall i \in \mathcal{S}, \tag{2}$$

where s_i is the capacity of parking lot i.

2. Demand satisfaction:

$$\sum_{i \in \mathcal{S}} x_{ij} + y_j = d_j \quad \forall j \in \mathcal{D}, \tag{3}$$

here d_j is the parking demand of household j.

3. Maximum walking distance:

$$x_{ij} \leq M_{ij} s_i \quad \forall i \in \mathcal{S}, \forall j \in \mathcal{D}, \tag{4}$$

where M_{ij} is a binary parameter defined as:

$$M_{ij} = \begin{cases} 1 & \text{if } c_{ij} \leq M \\ 0 & \text{if } c_{ij} > M. \end{cases} \tag{5}$$

4. Non-negativity:

$$x_{ij} \geq 0, \quad y_j \geq 0 \quad \forall i \in \mathcal{S}, j \in \mathcal{D}. \tag{6}$$

Here, s_i is the capacity of parking lot i, d_j is the parking demand of household j, and M is the maximum acceptable walking distance.

4.4 Algorithm Description

The demand and supply optimization process is implemented through a structured algorithm that efficiently assigns demands to available supplies while adhering to various constraints. This algorithm, as detailed in Algorithm 2, begins by loading the necessary input data, including supply capacities, demand requirements, and the cost associated with each potential assignment. It then formulates a cost matrix and applies constraints, such as maximum allowable distances and capacity limits. The optimization problem is solved using linear programming techniques, and the results are processed to generate detailed output metrics, which include the total assigned and unassigned demands, as well as supply utilization rates. This approach ensures that the optimal solution minimizes costs while satisfying all specified constraints.

Algorithm 2 Parking utilization optimization algorithm.

1: Load supply data, demand data, and the distance matrix.
2: Create mappings from supply IDs and demand IDs to their respective indices.
3: Apply a pre-calculated cost matrix to each pair from supply and demand data.
4: Create a mask to enforce the maximum distance constraint.
{Effectively preventing said pairs from being assigned in the optimization process.}
5: Adjust the cost matrix to include a small value to prevent ties (equally optimal solutions) in the optimization process.
6: Define the objective function to minimize the total cost of assignment, including penalties for unassigned demands.
7: Set up supply constraints to ensure the total assigned demand does not exceed the supply capacity.
8: Set up demand constraints to ensure the total received supply meets the demand requirements.
9: Solve the linear programming problem using an appropriate solver.
10: Extract the assignment matrix and unassigned demands.
11: Generate a detailed output of the assignments, including unassigned demands.
12: Calculate and report metrics on total demand, assigned demand, unassigned demand, supply utilization, and unfilled supply.
13: Save the results to the specified output files.
{The output files are the original Supply and Demand data but now include the assigned origins and destinations.}
14: Output the final results and execution time.

4.5 Optimization Process

The linear programming problem is solved using a high-performance solver to find the optimal allocation of parking supply to demand. The maximum walking distance (M) is a critical parameter that can be calibrated based on urban planning norms, empirical studies, or observed behavioural patterns (accepted maximum parking distance from surveys etc.).

Changing the penalty for exceeding the maximum walking distance constraint can also be used to model real-life behaviour (currently, pairs over the walking distance limit are not eligible, this can be charged as an additional introduced cost much like unassigned pairs). Setting the penalty lower would result in more households being assigned to parking capacity further away. Theoretically, an additional penalty for a higher walking distance could be set to be a multiple times higher penalty, to ensure that supply is not being assigned to demands above a certain threshold, but are being assigned for the first limit exceeded.

Changing the thresholds and penalties for exceeding them are the easiest ways that this model can be adjusted to suit specific behavioural patterns within the code. Additionally, the results can be greatly altered by adjusting parameters for calculating the distance matrix, e.g. only using specific types of infrastructure, adjusting speed/cost per links, etc.

4.6 Output and Interpretation

The tool generates comprehensive outputs including:

- For each household: Assigned parking location(s) and assigned capacity as a CSV using the original list of demand units.
- For each parking lot: Utilisation rate and served households as a CSV using the original list of supply spaces.

Key metrics derived from the results include:

- Percentage of satisfied demand (as well as nominal representation)
- Utilisation rate of parking supply (as well as nominal representations)

These outputs enable planners to evaluate parking allocation efficiently and further identify areas with parking shortages or surpluses. This will allow an assessment of the impact of changes in parking supply or demand. These metrics are the immediate outputs that are printed by the code, but since the most important outputs are the generated CSV files that return the complete list of demand points and supply points with assigned demands for supplies and supplies for demands, further detailed inspection is possible (and recommended) using GIS software solutions. Area statistics can be generated based on specific needs. For example, after running the code and assigning the results to the original data in GIS (QGIS used by the authors of this paper), we can analyse how the ratio of assigned capacity has changed for a specific residential area. The specific results and possibilities for a detailed inspection are presented in Section 5.

4.7 Tool Usage

To use the tool, urban planners or researchers should:

1. Prepare the required input data as described in the Data Requirements section. This includes creating the distance matrix and preparing the data into the required structure and format.
2. Specify the constraints, e.g., the maximum walking distance parameter based on local context or the scenario to be explored. Additionally, change the penalty (e.g., lowering it) or add an additional penalty with a higher threshold for “off-limits” walking distances.
3. Run the optimization process. The code was written for Python, specifically using the HiGHS solver accessed through the SciPy library.
4. Analyse the outputs to gain insights into parking allocation efficiency and accessibility. This includes reviewing the immediate printed results as well as joining the results to the original GIS data and inspecting each in detail.

By adjusting parameters or modifying input data and the process of distance matrix creation, users can explore various scenarios and their impacts on parking accessibility and utilization. This methodology provides a robust framework for optimizing urban parking allocation, offering valuable insights for efficient and sustainable urban parking solutions. However, users should be aware that the model assumes static demand (currently for a specific group of demand – residential parking) and its accuracy depends on the quality of input data. The model is, however, flexible, as stated, and can be adjusted to fit specific needs.

The code is not included in this paper. The general algorithm is described in Section 4.4.

5. Experiment

The experiment, to prove that this tool works correctly, was conducted on an example from the Czech municipality, Slaný. It is a Czech town near the Czech capital, Prague. The reason why this municipality was chosen is due to several factors. The town representatives and officers are currently deeply rooted in the topic of parking policy, the town has up-to-date data about parking places in the correct format (as well as residential data, which is the case for the entire Czech Republic) and the town is relatively small (around 18 thousand individuals), which makes it a lot easier to compute along necessary steps and more importantly, it is much easier to validate the results. Even though the town is smaller, it offers enough diversity, both in terrain and topology of buildings, to verify all unique cases for this tool. Those unique cases are discussed in Section 6.

For simplicity, only the current state of parking availability (designated as “Zero case”) and additional alternatives (referred to as “alternative scenario”, or “new”) are presented in this paper. While in reality, more alternatives were inspected, they do not offer any additional insight into how this tool works, their benefit is practical for the parking policy and development of the parking.

The tool was applied in the town Slaný in Czech Republic, using the address points that include number of citizens from 2021 state-wide data collection [6] adjusted for demand data by statistical distribution of cars for each address based on the state vehicle registry [24], parking lots (all legal parking spaces) represented by their centroids [32], and a distance matrix between each pair of supply (parking lots) and demand (address points) using Dijkstra’s shortest path algorithm using QNEAT3 in QGIS [28]. This provided a complete set of input data.

On the following figure (Fig. 1), the complete results of the current state were generated using the algorithm, see Section 4.4. As per the legend, the colour of the points indicate the ratio of demand serviced by supply and the size corresponds to the absolute value of demand. The points are households. Red areas indicate insufficient supply of public, legal parking spaces.

The computation time was 156.09 seconds on a moderately strong workstation (3,20 GHz processor with 4 cores and 8 logical processors – AMD Ryzen 5 1400 Quad-Core Processor, 16 GB or RAM).

On the following figure (Fig. 2), there are the complete results from an alternative scenario. The variations are limited to an increased parking capacity (demand) for a small parking lot (ID 209), originally with a capacity of 4 cars, newly 400 (a 396 car increase). This is of course not possible in real-life, but was chosen to demonstrate an extreme change in the urban environment. Combination of several (or individual) changes can be implemented that are much closer to reality. For

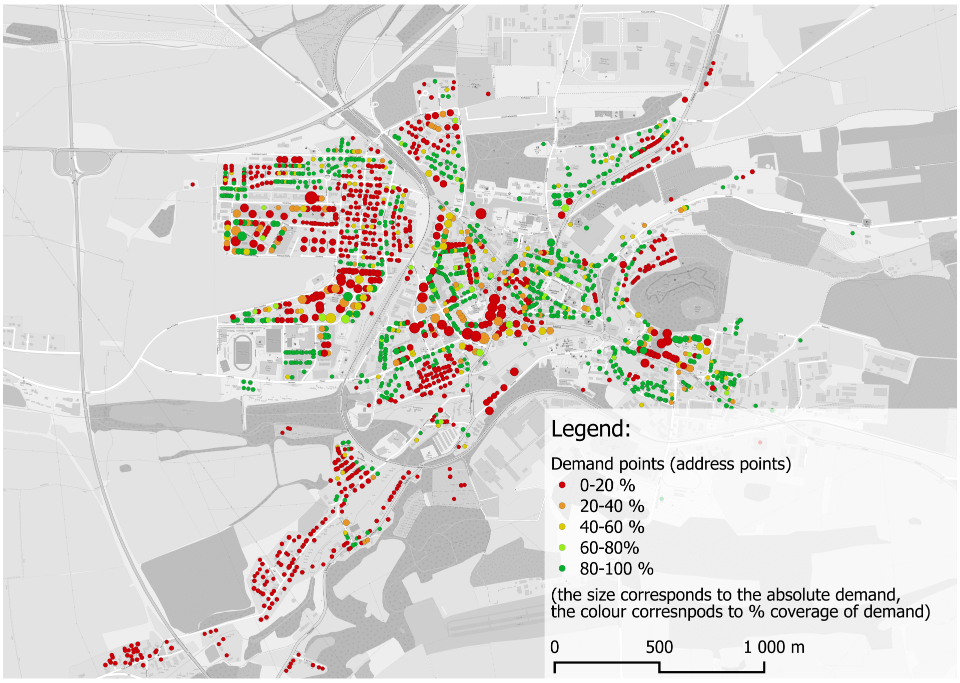

Fig. 1 *Zero case scenario evaluation.*

Demand Metrics:
Total Demand: 7356
Total Assigned Demand: 4050
Total Unassigned Demand: 3306
Assigned Demand: 55.06%

Supply Metrics:
Total Supply: 4294
Total Filled Supply: 4050
Total Unfilled Supply: 244
Filled Supply: 94.32%

those, the changes might be less noticeable. No new supply point was added to avoid computation of a new distance matrix. In reality, all variations of possible supply points should be created before the initial distance matrix computation for quick and comprehensive generation of alternatives.

The noticeable change is underlined in the generated map. Only surrounding buildings were affected and the new capacity was completely depleted.

The computation time was 159.96 seconds on a moderately strong workstation (3,20 GHz processor with 4 cores and 8 logical processors – AMD Ryzen 5 1400 Quad-Core Processor, 16 GB or RAM). The slight rise (3.87 s) in computing time to previous calculation is most likely random.

In the Fig. 1 we see how the tool was effectively used to evaluate parking space utilization in the form of distributing vehicles from households to parking capacities. One of the output files provide information about the filled capacities of the parking spaces, but all capacities near households are filled almost fully with only few exceptions. On the following Fig. 2, we see this tool applied to a simple

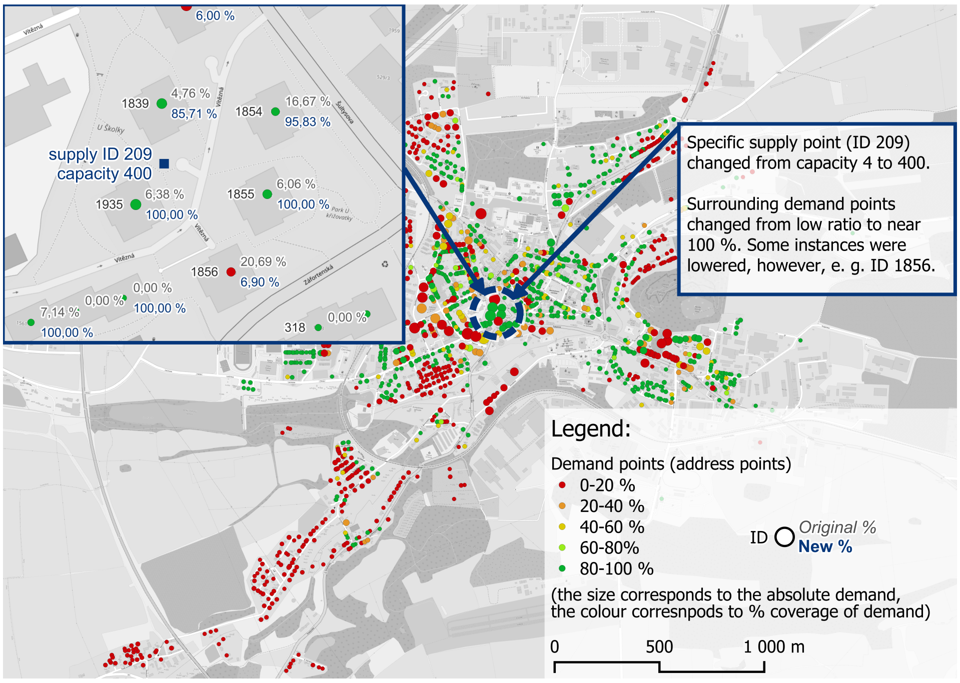

Fig. 2 *Alternative scenario evaluation.*

Demand Metrics:
Total Demand: 7356
Total Assigned Demand: 4446
Total Unassigned Demand: 2910
Assigned Demand: 60.44%
5% rise

Supply Metrics:
Total Supply: 4690
Total Filled Supply: 4446
Total Unfilled Supply: 244
Filled Supply: 94.80%
Logically also a rise, since all new capacity was used.

variation (scenario) with added parking capacity near highly occupied residential buildings (we can imagine that as an underground garage), and we can immediately see the impact of how the residents are redistributed. Using these outputs, we can either do an overview comparison of city-wide statistics, or we can go building by building, parking space by parking space or area by area and make separate, more granular, statistics and analysis.

6. Discussion

While there is no obvious problem with the code itself, the entire process relies heavily on data preparation and input quality. The data most prone to problems are infrastructure and demand points.

The infrastructure used in all experiment is from OpenStreetMap (the most accessible and complete open-source solution) that presents a lot of possible problems for automated usage such as this. Any problems can be avoided, if the infrastructure used for the distance matrix computation is provided by the municipality and corrected by a team of experts to be used as a replacement. Alternatively, HD maps from map service providers can be used. If these are not available, variations of a distance matrix creation need to be run and then inspected to find possible errors that should then be corrected manually. While this is relatively easy for a smaller town, it becomes progressively more difficult for larger cities. This opens up an opportunity to create an automated process for infrastructure correction and adjustment using open-source options such as OpenStreetMap.

Demand points are data that are usually not readily available. While the situation in the Czech Republic is quite good, it is not a standard situation to have resident distribution based on address points available. It is quite possible, this is not the case in most other countries. And even in the Czech Republic, it is only the residents that are available, not the cars. As described in the Data chapter, a simple statistical distribution was done for this purpose that utilises data from the state vehicle registry. Even here, there are a lot of possibilities for further research on how exactly vehicles are distributed based on the number of residents and type of the building, or other parameters such as placement, availability of public transport etc.

Besides the infrastructure, distance matrix, and distribution of demand, four main points for consideration were defined by the authors:

1. Specific address points may have many residents but potentially few vehicles (nursing home, etc.) – it is possible to manually adjust the number of vehicles at these points based on surveys.

2. Address points that have high parking demand but no residents (employment, offices, shops) – can be added separately and included in the address point layer. This is a good opportunity for further research on a similar tool that investigates other types of parking instead of residential.

3. Private lots and properties – single family homes often use (and should use) parking on their property. It is possible to add the address spaces of family houses to the centroid layer of the passport and replace their capacity with 1-2 parking spaces. By definition, they will always be used by the house in question, as this is a minimization task.

4. Private garages (batteries of garages) – the way to work with these capacities is not clear, as they are private lots that only constitute potential parking capacity.

All of the four points above fall into the data preparation phase, further signifying just how important it is to prepare the data well. Specific research can be conducted in this regards to find the best possible data inputs for specific scenarios or use cases. This paper focuses solely on the tool.

Positively, this tool can also be used to analyse the changes in parking capacity availability based on infrastructural changes, since it directly uses the real-life infrastructure. It can also include detailed changes such as improving pavement or realigning parking space demarcation if the criteria for distance matrix (or cost matrix) are set correctly.

7. Conclusion

The parking allocation optimization tool presented in this paper offers a powerful and flexible approach to addressing the complex challenge of residential parking management in urban areas. By leveraging linear programming techniques and adapting the transport problem from Graph Theory, this tool provides a quantitative basis for evaluating parking accessibility, utilisation and assignment.

The experiment conducted in Slaný demonstrates the tool's capability to analyse current parking situations and assess the impact of potential supply changes. The results highlight the tool's effectiveness in identifying areas of parking shortages and surpluses, as well as quantifying the benefits of new parking capacities.

Key strengths of this approach include its adaptability to different urban contexts through parameter adjustments, its ability to process large-scale data, and its provision of both macro-level statistics and detailed allocation maps. These features make it a valuable asset for urban planners and policymakers in developing evidence-based parking strategies.

However, the study also reveals important considerations for future development. The tool's effectiveness is heavily dependent on the quality and accuracy of input data, particularly the infrastructure data used for distance calculations and the demand data representing vehicle ownership patterns. This highlights the need for further research into data preparation methods and potential integration with more sophisticated demand modeling techniques [33].

Additionally, while the current focus is on residential parking, there is potential to extend the tool's application to other types of parking demands, such as commercial or mixed-use areas. This would require additional research into modeling different parking behaviors and time-dependent demand patterns.

In conclusion, this parking allocation optimization tool represents a significant step forward in quantitative approaches to urban parking management. It provides a solid foundation for decision-making in parking policy and urban planning, while also opening avenues for further research and development in the field of urban mobility and spatial optimization.

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Author Contributions

R. Dostál is the leading author of this publication with the biggest contributions to the text and working code, followed closely by V. Kremlík and A. Johanidesová. J. Kocourek and A. Dostálová contributed equally.

Conflicts of Interest

The authors declare no conflict of interest. The funding organizations had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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