Aalto University
MS-E2177 - Seminar on Case Studies in Operations Research

Optimizing bus parking to enhance electric bus usage

Final report

Esa Honkamaa
Elias Pelo (Project manager)
Olli-Pekka Pennanen
Anton Rühr
Julia Virtanen

May 14, 2025

Contents

1 Introduction

1.1 Background

Running a public transport bus service in Finland is a highly competitive business. Government contracts for bus services are awarded through competitive tendering, which forces private companies to operate as efficiently as possible. Although natural regional monopolies often develop over time, operators must optimize their time and resources to secure new contracts, maintain profitability and prevent new competitors from entering the market.

Our client, Koiviston Auto, is the largest bus operator in Finland. Founded in 1928, the company has a long history and plays a central role in public transportation system in Finland. Today, it operates a fleet of over 1100 buses and has more than 2500 employees across the country (Koiviston Auto, 2025).

Koiviston Auto provides local, regional and long-distance transportation services, making it an essential part of daily travel for numerous people. The company has also taken significant steps toward sustainable transportation, aiming to have 50% of its urban fleet fully electric by 2028 (Koiviston Auto Group, 2024).

Bus companies need to be highly efficient to remain competitive. Their processes must be cost-effective with focus on minimizing expenses. Optimizing processes is important in the public transportation sector. Strict regulations apply to bus operators and violations can result in significant penalties. Additionally, switching to electrical busses is an efficient way to reduce costs and also strengthen sustainability which aligns with Koiviston Auto's vision. Electrical buses are not only more ecological to use, but also more economical because of the high fuel consumption and the rising oil prices as discussed in Lajunen (2014). Electric buses bring significant benefits but they also present a major challenge: charging them efficiently can be difficult given their heavy use throughout the day. Charging often requires several hours and the infrastructure needed is both costly and limited. As a result, bus operators must manage their charging capacity carefully and plan charging schedules as efficiently as possible.

In this project, we aim to develop an optimal parking strategy within the depot that ensures that all electric buses have sufficient charge before they depart for their assigned routes. The solution must be resilient to uncertainties such as variable arrival times.

1.2 Objectives

The main goal of the project was to automate the process of developing an allocation plan for each bus to the client's bus depot in Jyväskylä. The ultimate goal was to develop a general tool to perform automatic allocation in any depot only giving different parameters of the depot for the model. So far, this allocation has been performed manuyally approximately three times per year for each depot, which takes up a lot of time from the employees.

There were also specific goals for the allocation plan formed by the model. It should be very robust against the many uncertainties associated in bus parking at the depot. The buses arrive at the depot at different times than they are planned for multiple reasons and some buses might be broken and needed to switch to different bus. A poorly developed plan negatively impacts operational efficiency and the day-to-day of the bus drivers when one cannot access the bus they need since it is, for example, blocked by other buses ahead of it in the depot.

The project objectives were meant to be achieved by utilizing mathematical methods such as optimization with a thorough sensitivity analysis to be done afterward to ensure robustness of the allocation plan against the many uncertainties like the stochastic arrival times of the buses to the depot. At the end of the project, the goal is to have a ready-to-use mathematical model, which the client could then use to develop robust allocation plans for their depot in Jyväskylä, and if possible, the model should be easily adapted to other depots.

1.3 Specific scenario of problem: Jyväskylä depot layout

The structure of the depot is shown in Figure 1. The depot consists of two distinct parking areas: an outdoor section with 17 parking spaces equipped with electric chargers and an indoor warehouse area. The warehouse has 12 lanes each containing 6 parking spots. Out of the 72 indoor spaces, 51 are equipped with charging points while 21 do not have chargers.

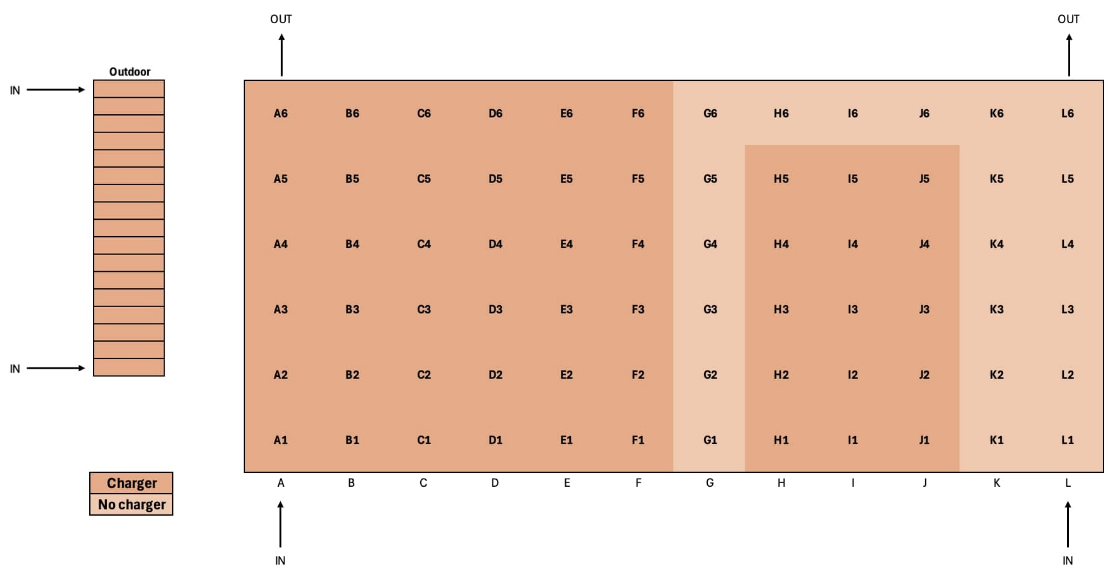

Figure 1: Bus depot layout

The outdoor parking spaces do not pose major challenges as buses can enter and exit without restrictions. The main challenges occur in the indoor depot, which introduces significant constraints. Buses enter from one end and exit from the other, meaning that once a bus is parked it can only leave if no other buses are blocking the exit. This makes it critical to ensure that buses scheduled for early departures are not parked behind others.

The wide variety of buses adds complexity to the problem. In total, there are eight different bus types that need to be considered. These buses differ in fuel type (electric, diesel), length and color. Some are designed for city routes, while others are used for long-distance travel. The City of Jyväskylä has set strict rules regarding route operations. Using the wrong type of bus, being late or missing scheduled shift can lead to financial penalties. Each shift requires a specific type of bus to meet these regulations. Therefore, the allocation plan must ensure that buses of the correct type are available for each shift and they are parked so that they can leave the depot on time for their shifts. It is crucial that electric buses are allocated to parking spots with charging points. Otherwise, they can not be charged overnight and will not be able to operate their shifts the next day.

In addition, the bus schedules change throughout the week. On weekends, fewer buses are in operation. Table 1 shows how many buses of each type are in operation each day. This highlights the drop in the total number of buses running during the weekend. This makes parking more difficult, since some of the lanes do not empty during the day. Since the lanes do not empty on the weekend, blockages are more likely to form. This makes departures more difficult when all buses need to be back in service. The allocation model must ensure smooth parking and departure during these problematic periods.

Table 1: Bus types in operation during the week.

	Mon – Thu	Fri	Sat	Sun
DMS	3	3	0	0
DMV	26	28	0	0
DTV	4	4	0	0
SMS	17	17	17	17
SMV	22	22	22	21
STS	8	8	1	1
STV	14	14	6	3
SVV	3	3	3	3
Total	**97**	**99**	**49**	**45**

2 Literature review

At the start of the project, our first objective was to review existing literature and learn from previous research and methodologies for similar situations. There are similar problems in other research fields so we did not limit our research only to literature around bus depot management as there might be good insights to our specific problem from different fields. In this part, we explore literature sources and what kind of benefits different methods have but also limitations to our usage case.

2.1 Similar problems from different fields of research

There have been some studies of the closely related problem of tram dispatching problem (TDP) and different kinds of models to address this issue have been presented in literature. For example Winter and Zimmermann (2000) presented methods for TDP where number of individual maneuvers (shunting moves) or type mismatches are minimized. They have a lot in common with the bus dispatching problem and similar goals could be taken as an objective function with buses. They are a useful starting point to develop models for bus dispatching and depot parking planning. They have some differences to buses, which weakens the direct applicability of these models to bus depots. In TDP, lanes are respected as stacks instead of queues. Thus, if we need to switch the order of one queue of buses, we need to move the whole queue out. With trams the required number of moves depends on the needed change in the order of trams in a stack.

Parking of autonomous cars in a parking facility is studied in Bahrami and Roorda (2020). This problem holds multiple similar features as bus dispatching problem. The model minimizes the total number of relocation movements inside parking facility. In this model both arrival and departure times for each car are stochastic. The model also allows that some cars departure before all cars of a facility have arrived. In most bus dispatching models this is an important assumption. In our scenario not all buses leave the depot during the weekend which conflicts with this assumption. The model in Bahrami and Roorda (2020) has some other assumptions which prevents it from being used in our model. In our model different buses can take different bus ID, the only constraint is that the type of a bus needs to be specific one. In the model in Bahrami and Roorda (2020) this is not allowed, which limits the number of feasible solutions.

2.2 Bus dispatching problem (BDP)

Literature on depot management provided us insights into methods taking into account stochastic bus arrival times. In general, bus dispatching problem (BDP) was defined in Hamdouni et al. (2007b) as follows: "buses of different types arrive at a depot in the evening and must be parked immediately upon their arrival in such a way that, during the next morning, they can be dispatched directly (that is, without moving other buses to clear the way out for a bus) to departure routes, each of them requesting a specific bus type". There are a few different models in literature for bus dispatching problem (BDP) which all have different strengths and limitations. We could not find any solution which would work for our instance in Jyväskylä depot directly as all models had limitations and took into account different things.

We will now present the most relevant models from literature which solve different versions of BDP. Since moving buses to clear the way for other buses after parking is not desirable, we focused on methods ensuring buses can be dispatched directly without delays. There are also two type of these models, deterministic and stochastic. Deterministic models assume that buses have predefined arrival and departure times. In stochastic models the arrival times may vary as in real life this is often true. As robustness of the developed model was a major objective, we also concentrated on stochastic models in our literature review.

2.2.1 Deterministic methods to solve BDP

Model to solve BDP using block patterns is presented in Hamdouni et al. (2006) where the number of lanes needing rearrangement are minimized. BDP might not be feasible if we limit out the option to do rearrangements, so this model gives option for this. Lane patterns mean how different bus types are ordered in a lane, for example AABB or ABAB where A and B are different bus types. Research in Hamdouni et al. (2006) also shows that robustness of patterns increase when minimizing breakpoints in a pattern. Breakpoints are formed when bus type changes in a pattern. For example AABB has one breakpoint and ABAB has 3 even though both patterns hold two different bus types. Robustness means that the chosen pattern stays still applicable if buses arrive in different order to depot from the planned one which is very common in reality.

Hamdouni et al. (2006) builds three different models for BDP using pattern structures. In two models of these rearrangements of lanes are possible. In the first one, the rearrangement can be arbitrary so that the patterns can be anything formed by maximum of two different bus types. In the second model, the rearrangements are needed if a formed pattern is not a one or two block pattern (contains maximum of one breakpoint). The first objective is to minimize the number of needed rearrangements. The second objective is to minimize the number of patterns with two different bus types which means preferring one-block pattern lanes as these are the most robust solution.

Hamdouni et al. (2007a) builds on the models in Hamdouni et al. (2006) with a model, where rearrangements are not allowed during the night. If correct bus types are not available, there is a mismatch and a wrong type of bus is taken for the route. This model minimizes these mismatches. It also allows only as admissible lane patterns one or two-block patterns, as these provide the most robust solutions when buses are not coming in the planned order to a depot.

So far, the models above do not take into account the charging of electric buses when planning parking in a depot. There is not much literature around it in general. One exception is the model from Azema et al. (2024), which uses constrained programming to solve how electric buses should be assigned for different trips and same time planning how charging can be achieved such that each bus has enough energy to finish the assigned trip. The model also can take into account multiple days and plan dynamically the system without making assumption that all buses need to arrive before some leave and it can have longer planning horizon than only one day.

The model from Azema et al. (2024) does not have objective function which means it does not optimize anything, it only seeks to find a feasible solution. The model also has added some practical constraints for example that only some of the chargers can be used same time. This approach is promising in some ways, but we decided not to use it as a base for our solution as it assumes all buses are homogeneous and electric, which is one of the main difference to our scenario and would make it hard to adapt to our situation. It also assumes that there are chargers on each parking slot. In addition, this model is not the most robust one. It does not optimize how buses should be parked to increase probability that plan still works if their arrival times differ from planned ones as previous models do.

2.2.2 The k-position approach

Next, we describe two methods to solve a stochastic BDP. Both were introduced in Hamdouni et al. (2007b).

The k-position approach provides a robust solution for the BDP problem, when the arriving buses to the depot shift by at most k positions from their planned arrival position. The k-position approach is formulated using admissible patterns, which is an enumeration of all admissible lane patterns. Hamdouni et al. (2007b) allow for only lanes with maximum two different "blocks" of buses for each lane. This means that e.g. if be have bus types of A and B with lane length of 5, lanes AAAAA (one-block pattern) or AABBB (two-block pattern) are possible, but e.g. a lane ABBBA (three-block pattern) is not. This is also a weakness for the model, because it limits possible parking configurations for the buses. We call the blocks as an *exit* block (closest to the lane exit) and an *entry* block.

We denote the bus type by t, the arrival position by i, arrival scenario by S and the set of all arrival scenarios by S^k. We define the following variables as minimum and maximum number of type t buses arrived when arrival in position i has just arrived, i.e.,

$$\overline{a}_i^{kt} = \max_{s \in S^k} d_{is}^t, \quad \forall t \in T,\ i \in I$$

$$\underline{a}_i^{kt} = \min_{s \in S^k} d_{is}^t, \quad \forall t \in T,\ i \in I.$$

The arrivals can deviate by at most k positions. This can be formally stated by the formula below, defining the extreme values for $\overline{a}_i^{tk}$ and $\underline{a}_i^{tk}$, where $\sigma_s(i)$ denotes the position of ith arrival in the planned arrival scenario s:

$$i - k \leq \sigma_s(i) \leq i + k, \quad \forall i \in I.$$

Both $\overline{a}_i^{tk}$ and $\underline{a}_i^{tk}$ are non-decreasing w.r.t. to i. We denote by I_k^t the set of indices, where this sequence increases, that is, $I_k^t = \{i \in I \mid \overline{a}_i^{tk} > \overline{a}_{i-1}^{tk}\}$. We do not need to consider all scenarios in S^k, but rather only the extreme ones, where all arrivals are moved either forwards or backwards by the maximum amount. All departures are deterministic, so the maximum and minimum values for the number of buses departed are all the same. The departures are defined by variables d_j^t, j and J_k^t, corresponding to the respective variables for arrivals.

Let b_t be the number of buses of type t and v the number of lanes. Further, we denote the set of all admissible patterns by P and the set of two-block patterns by P_2. For each pattern p, we denote the number of buses of type t in its exit block (resp. entry block) by o_p^t (resp. e_p^t). We denote the number of lanes partitioned according to p by X_p. Finally, we denote by variable Y_{pi} (resp. Z_{pj}) the number of lanes partitioned according to pattern $p \in P_2$, whose exit block (resp. entry block) is full, when the arrival in position i (resp. departure j) has just been parked (resp. left).

The k-position approach is a feasibility problem, in which choosing a large value for k may cause problem being infeasible. Objective function can thus technically be freely chosen. Hamdouni et al. (2007b) decide to minimize the number of two-block lanes, because one-block lanes facilitate the operations and makes it easier to plan parking similarly as in previously discussed model. The full k-position approach formulation from Hamdouni et al. (2007b):

$$
\begin{aligned}
\text{Minimize} \quad & \sum_{p \in P_2} X_p && (1)\\
\text{Subject to:} \quad & \sum_{p \in P_2} X_p = v && (2)\\
& \sum_{p \in P_2} (o_p^t + e_p^t) X_p = b^t, \quad \forall t \in T && (3)\\
& \sum_{p \in P_2} o_p^t X_p + \sum_{p \in P_2} e_p^t Y_{pi} \geq a_i^{kt}, \quad \forall t \in T, i \in I_k^t && (4)\\
& \sum_{p \in P_2} o_p^t Y_{pi} \leq a_i^{kt}, \quad \forall t \in T, i \in \bigcup_{u \in U} I_k^{ut} && (5)\\
& Y_{pi} \leq Y_{p(i+1)}, \quad \forall p \in P_2, i \in J \setminus \{n\} && (6)\\
& Y_{pi} \leq X_p, \quad \forall p \in P_2 && (7)\\
& \sum_{p \in P_2} o_p^t X_p + \sum_{p \in P_2} e_p^t Z_{pj} \geq d_j^t, \quad \forall t \in T, j \in J^t && (8)\\
& \sum_{p \in P_2} o_p^t Z_{pj} \leq d_j^t, \quad \forall t \in T, j \in \bigcup_{u \in U} J^{ut} && (9)\\
& Z_{pj} \leq Z_{p(j+1)}, \quad \forall p \in P_2, j \in J \setminus \{n\} && (12)\\
& pn \leq X_p, \quad \forall p \in P_2 && (10)\\
& X_p, Y_{pi}, Z_{pj} \in \mathbb{N}_0 && (11)
\end{aligned}
$$

Our explanation here is significantly shortened from Hamdouni et al. (2007b). We refer to the original paper for details.

2.2.3 Stochastic approach

An alternative for the k-position approach is the stochastic approach, which minimizes the expectation of a function positively correlated with the number of buses that make the planned solution infeasible because they arrive too late or too early. This approach from Hamdouni et al. (2007b) takes arrival times into account and assumes that these arrival times follow e.g. a triangular function (any type of function can be chosen), with the mode being the listed arrival time from the default scenario. A large number of arrival scenarios are then simulated, because an analytical solution can not, in general, be found. The problem is then formulated as a sufficiently similar integer programming problem to the k-position approach. The main difference is in the objective function: it seeks to minimize the number of arrivals (according to simulations), where too many or too few buses of any type t have arrived at that time and thus cannot be parked.

A more in-detail explanation with formulas is found from Hamdouni et al. (2007b). For us, the k-position approach was sufficient from these two stochastic BDP models, and we thus decided not to implement the stochastic approach. However, it can provide more reasonable solutions, if the timetables have some very dense sections with lots of arrivals within a short period of time. These sections can require more flexibility than what can be found in solutions given with the k-position approach. In addition, the k-position approach can be limited by single arrivals that act as "bottlenecks", while the stochastic approach can be more balanced. The stochastic approach can perform well in situations where a feasible solution is more difficult to find. Overall, however, these were not relevant issues for us, and our solutions would have likely been somewhat similar regardless of which method was used.

3 Data

The project was conducted based on the data received from Koiviston Auto. They provided us with comprehensive data to help us understand how they operate the bus depot. Based on the data, we managed to identify the key problems that needed to be taken into account when approaching the problem.

Koiviston Auto shared us the depot layout and their initial approach to solve the allocation. Their preliminary approach offered valuable insight into the existing system and showed some of the issues. The depot layout included data on the different types of busses in the depot. The buses are categorized based on combinations of characteristics such as fuel type, vehicle size and axle configuration. Each unique combination defines a specific bus type. Koiviston Auto uses a color coding system to indicate how they have allocated the bus types to the depot so far. Data also included information on how many vehicles existed in each category. Our clients original approach and the depot layout gave us a better understanding of the problem. We chose to use a similar strategy to minimize the variety of vehicle types in each lane.

One of the key challenges in the allocation process is to ensure that electric buses are assigned to the correct parking spots so they can be fully charged overnight. Koiviston Auto provided a detailed map showing which parking spots are equipped with charging points. This was essential for understanding how electric buses should be distributed within the depot. The map also showed how the chargers are connected. Each charger is linked to four parking spots, meaning that a maximum of four buses can be charged at the same time using one charger. It is important to note that charging efficiency is higher when fewer vehicles are connected simultaneously. However, the client stated that overnight charging is not a problem, even when all four spots are occupied. Therefore, fixing these charging spots for electric buses in our optimization problem ensures that they will be fully charged and ready to complete their shifts.

As a crucial component of the optimization to solve the allocation problem, Koiviston Auto provided us with detailed schedule data covering each day of the week. The schedules are identical from Monday to Thursday, while Friday, Saturday and Sunday each have their own separate schedules. In total, we received four datasets each corresponding their unique schedule. These datasets form the pillars of our allocation algorithm, as they capture the essential information necessary to fully understand and optimize the bus operations. The data includes various key variables critical to form comprehensive picture of the operational schedule. Each row of represents a specific stop along a shift's route. The data is organized by a unique shift identification code and for each shift the earliest row indicates when the bus leaves the depot. The following rows correspond to the sequence of stops along the route and the final row shows when the bus returns to the depot. For our purposes, the key information is when the bus departs from and returns to the depot. Table 2 lists the main variables for our purpose form the dataset. Later in this analysis, we explore how this data is used in the allocation algorithm. The identification code tells us the required bus type, while the departure and arrival times help us allocate buses efficiently and avoid blockages in the depot.

Table 2: Key variables from the driving schedule.

Variable	**Explanation**
Shift ID	Shift identification code defining a shift of a bus, regardless of which specific bus operates it. The identification code contains information about the type of bus required for each shift.
Operating day	Days of operation indicating when the schedule is active
Departure stop	The first departure from the depot
Departure time	The time the shift starts from the depot
Arrival stop	The final return to the depot
Arrival time	The time the shift ends at the depot

Koiviston Auto also provided us documentation about the regulations and penalties. This outlined the specific requirements for each shift the operating bus needs to fullfill. Breaking the regulations results in fines. For example, using the wrong type or colour of bus, being late or missing shifts can lead to financial penalties. Knowing these rules was important for building the allocation model, because avoiding penalties directly affects efficiency and costs. It also gave us a good idea of which regulation breaches are very costly and which ones might be acceptable if needed.

3.1 Modifications to data

The original dataset was primarily focused on the day to day schedule of the bus fleet. It included detailed information on when each bus arrived and departed the depot the same day. Since our objective was to focus on that the busses are able to succesfully park in the evening and leave the next morning, we decided to change our perspective. Instead we looked when the bus arives that day and when it leaves the next day. We modified the data to suit this scope. The original data included mid-day charging events, where buses briefly return to the depot during service hours. We decided to exclude these charging stops from our model, as they were not our main goal.

Koiviston Auto had informed us that three of their buses were marked with the system id "SVV", indicating a new vehicle type that had not yet been fully integrated into their internal systems. To ensure compatibility with our model, we reclassified these buses using the "SMV" system id, which the system could interpret correctly. At the same time, we preserved the original identification numbers so that these specific vehicles could still be recognized and tracked throughout the dataset.

We also made several changes to the depot layout representation. The original layout included two additional lanes, one designated for buses under repair and one for long distance buses. Since these were not within the focus of our work, we excluded both of these lanes from the model. Additionally, the datagrid was adapted to generate as many outdoor parking spots as necessary to accommodate all buses, simulating overflow parking when the main depot lanes reached full capacity.

4 Methods

4.1 Modified k-position approach

The core of our bus parking optimization system relies on an implementation of the k-position approach model Hamdouni et al. (2007b). After reviewing literature as discussed in Section 2, we decided that this model served as the best solution for our problem. Our modified k-position approach builds on the foundation of the original model while introducing several extensions to handle the constraints unique to the scenario Koiviston Auto has at their depot. At the heart of our case specific modifications were the additional pattern constraints. First type of additional constraint concerns the case, where the depot in question has m lanes which can only hold some subset of bus types $T' \subset T$, where T denotes the set of all bus types. This can be due to many reasons including physical limitations like size of some bus types exceeding the size of the spots of that lane. Denote by $P' \subset P$ those sets of patterns, which have only bus types $t \in T'$. Adding the following constraint (12) ensures that this case is handled properly,

$$\sum_{p \in P'} X_p = m. \tag{12}$$

This constraint can be adapted to more complex cases such as lanes where the m lanes in question are heterogeneous, meaning that the spots of the lane can hold some subset of bus types but other spots some differing subset of bus types. In such cases, it is sufficient to construct a subset of patterns P', which do not violate such constraints for these lanes and then add constraint (12) to the model. This framework is clearly a very flexible tool for adapting the model to work with the highly specific needs of real world bus depots.

The original model is configured to create a grid of parking spots where each lane is of the same length. The scenario at Koiviston Auto's depot required us to take outdoor parking into account. The outdoor parking differed from the depot by its layout, as previously discussed inside the depot the buses are in a queue meaning no bus can leave until all buses ahead of it have left the depot. This is not true for the outdoor parking in our case where the buses are parked side to side. This can be modeled with lanes of length 1 having only an exit block and no entry block. More generally suppose you have m' lanes of length l' where only bus types $t \in T'$ can be parked. Here additional block patterns P' having only bus types $t \in T'$ of length l' need to be generated and then one can implement a similar constrain as in 12 to assure that the model selects the wanted number of such patterns to accommodate these lanes having a different length from the main lanes of the depot.

4.2 Solving (M)ILP model with HiGHS solver

Solving (M)ILP models means optimizing a linear objective function subject to a set of linear constraints, where (some or) all variables are required to take integer values:

$$\begin{aligned} \text{maximize} \quad & c^\top x \\ \text{subject to} \quad & Ax \le b, \\ & x_i \in \mathbb{Z} \quad \text{for some } i. \end{aligned}$$

The HiGHS solver is a state-of-the-art open-source tool capable of efficiently solving large-scale LP and MILP problems. It uses advanced techniques such as presolve routines, dual and primal simplex, and interior point methods for the LP relaxation, followed by branch-and-bound and cutting planes for handling integrality constraints.

When solving ILPs with HiGHS, the process typically begins with solving the LP relaxation, i.e., ignoring the integer constraints to find a bound for the objective function. If the LP solution violates integrality, HiGHS enters the branch-and-bound phase, where the solution space is recursively divided into smaller subproblems by adding integer constraints and resolving. This tree-based search continues, potentially enhanced by cutting planes, which are inequality constraints that remove fractional solutions without excluding any feasible integer solutions.

Open source solvers have become faster in recent years although for MIP problems, there still seems to be a quite significant performance gap between the best commercial solvers and the best open-source solvers such as HiGHS.

4.3 Parking and dispatching algorithm

After obtaining an optimal solution to the modified k-position approach model presented in 4.1 one must obtain an optimal assignment of the arrivals and departures to individual spots in the lanes. The procedure to accomplish this is presented in Hamdouni et al. (2006), which also includes a detailed proof of the correctness of the following algorithms. Firstly a list of lanes L_t is constructed for each bus type t as described in Algorithm 1. The lanes L having different patterns $p \in P$ are sorted with priority given by the values $Y_{p,i}$. Denote by P^t the set of two-block patterns with exit block of type t.

Algorithm 1 Constructing list of lanes

Inputs: $P^t,\ Y_{pi}$
Output: L_t
$m_0^t \leftarrow 0$
for $i = 1$ to n **do**
  $m_i^t \leftarrow \sum_{p \in P^t} Y_{p,i}$
end for
$I \leftarrow [\,]$
$i_{\text{prev}} \leftarrow 0$
for $i = 1$ to n **do**
  if $m_i^t > m_{i_{\text{prev}}}^t$ **then**
    append i to I
    $i_{\text{prev}} \leftarrow i$
  end if
end for
$L_t \leftarrow [\,]$
for each $i \in I$ **do**
  for each $p \in P^t$ **do**
    $\Delta \leftarrow Y_{p,i} - Y_{p,i-1}$
    if $\Delta > 0$ **then**
      Append Δ lanes of pattern p to the end of L_t
    end if
  end for
end for
return L^t

After constructing the lists of lanes L_t for each bus type t, the arrivals are assigned to specific slots according to Algorithm 2. This algorithm assigns arriving buses to specific spots in the depot by prioritizing the exit blocks of two-block lanes, then one-block lanes and finally entry blocks of two-block lanes. This priority order assures that given an optimal solution to the k-position approach, a feasible parking plan can be obtained when the arrivals do not deviate from the planned arrivals by more than k positions.

Algorithm 2 Parking algorithm

Inputs: Bus of type t, ordered list of lanes L_t
Output: Parking location for the bus
for each lane $\ell \in L_t$ **do**
  if exit block of ℓ is not full **then**
    Park the bus in the exit block of lane ℓ
    return
  end if
end for
if there exists a one-block lane of type t that is not full **then**
  Park the bus in the available one-block lane
  return
end if
Park the bus in an entry block of type t

Once you have parked the buses, you then have to assign them to new tasks for the next day according to the planned departures. The dispatching algorithm in Algorithm 3 is the mirror image of the parking algorithm presented before in Algorithm 2. First, as before, construct ordered lists of lanes this time denoted by L'_t for each bus type t, this time given priority by the values $Z_{p,j}$ instead of $Y_{p,i}$.

Algorithm 3 Dispatching algorithm

Inputs: Bus type t, list of lanes L'_t
Output: Dispatch location for the bus
for each lane $\ell \in L'_t$ **do**
  if exit block of ℓ is not empty **then**
    Dispatch the first bus in the exit block of lane ℓ
    return
  end if
end for
if there exists a one-block lane of type t that is not empty **then**
  Dispatch the bus from that one-block lane
  return
end if
Dispatch the bus from an entry block of type t

5 Results

The implemented system is an approach to solve the problem of distributing parking patterns for buses in a bus depot. The system can be found on GitHub (Pennanen et al., 2025). The system parses bus routing data and implements a two-phase optimization for the bus allocation in the depot. This implementation provides solutions for optimizing the bus parking and electrical bus charging at the depot.

Section 5.1 presents the results for weekdays when all buses in the depot move. Additionally, it highlights the effectiveness of the model in cases where the depot is emptied during the day. Section 5.2. presents the results for the weekends when only part of the buses move in the depot. Maximum deviation of 5 was used with the k-position approach model.

5.1 Model for the weekdays when all buses move

Weekday operations aligned most closely with the original model's assumptions. This is primarily because the k-position approach model is designed under the assumption of full-scale operation of the buses. This means that the model assumes that every bus is scheduled to depart and arrive back during the day. Therefore, all parking spaces are active and there are no buses in the depot that could block the departure or arrival of another bus.

The full-scale operation of the buses and the consistency in bus scheduling allowed the k-position approach model to function effectively. The model yielded feasible solutions and selected patterns based on case-specific constraints. The end solutions and the selected block patterns are represented in Figures 2 and 3. After computing the block patterns the system uses heuristics to assign specific buses to the block patterns as presented in Hamdouni et al. (2006). The parking algorithm efficiently assigns arriving buses to optimal lanes by prioritizing same type exit blocks and utilizing entry blocks as overflow. Additionally, dispatching algorithm is used to generate dispatch sequences.

The system successfully optimizes bus parking for weekday operations. When evaluating the quality of bus allocation in the depot, it is reasonable to examine whether buses can park and depart from the depot according to the schedule. This is achieved in our allocation, which is to be expected since the models are designed around these operational conditions. The weekday optimization performs reliably because the k-position approach model and the algorithms inherently assume full daily turnover.

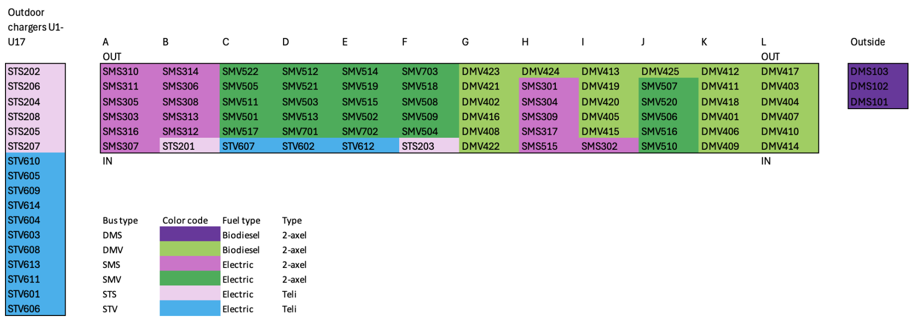

Figure 2: Parking results on weekdays

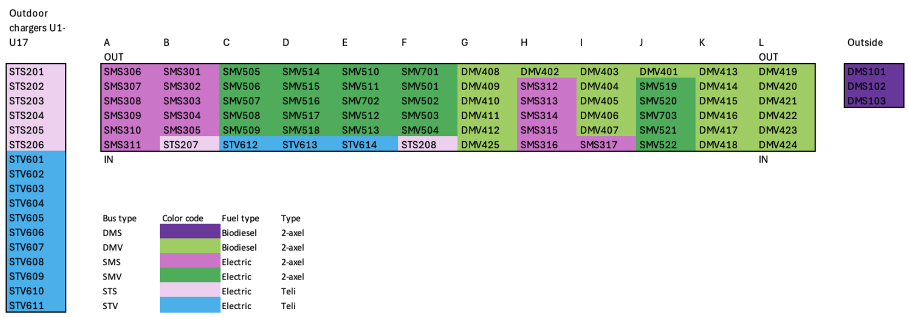

Figure 3: Dispatching results on weekdays

5.2 Model for the weekends when only part of the buses move

Weekend operations presented significant challenges for the k-position approach model. Unlike weekday scenarios, in which all buses are in operation, weekend schedules involve only a subset of the fleet being operational. This means that the remaining buses are stationary in the depot. This fundamental difference conflicts with the assumption of the k-position approach model which presumes full depot being operational.

The model gives infeasible solutions for the weekend operations, when it faced stationary buses that do not have departure or arrival data. On the contrary, this is to be expected since the original model does not account for permanent blockages in parking spaces. The stationary buses effectively create fixed obstacles that disrupt the optimal allocation patterns established for weekday operations.

The weekend operations are performed with electrical buses only. The root causes for the solution's infeasibility are the biodiesel buses on depot lanes H, I and J that block electric buses from weekend operations as shown in Fig 3. To address this limitation, the input data could be modified to better align with model assumptions. By restructuring the bus scheduling sequence the model could yield feasible solutions. Specifically, we could set the departures and arrivals of the biodiesel buses first in the corresponding sequences.

Additionally, there is another way to structure the weekend operations in the depot. There are six fully electric six bus lanes in the depot. Our research suggests that the more optimal way of performing weekend operations would be to operate only with the full lanes of electrical bus capacity and replace the overflow buses on lanes H, I and J with STS or STV type buses from the outside charging spots. These outside charging spots are single bus units. Therefore, they do not have the same constraints as the lanes in the depot hall. In this way Koiviston Auto would be able to enhance operational flexibility during weekends, including easier interim charging during the shift.

5.3 Model limitations

During the development of the scheduling model, several limitations were identified. The limitations affected both its flexibility and its ability to generalize to other scenarios. A central assumption in the model was that all columns or parking lanes in the depot would empty over the course of the day. This assumption generally held on weekdays, but weekends caused trouble. Due to fewer buses operating during weekends, many columns remained partially filled. This led to infeasibility in the model's logic.

Another key assumption was that the last bus would depart from the depot before the first one returns. This assumption avoids overlap and potential conflicts. However, this condition did not hold in all cases. During the weekdays there were some buses that operate only a couple hours in the morning. They often return to the depot before the last buses have departed. This disrupted the expected flow and caused scheduling conflicts that the model was not designed to handle.

In addition to these structural assumptions, the model was highly sensitive to the definitions of manual constraints. Due to the number of buses in operation, constraints had to be implemented manually for the specific scenario. This closely tied the system to the specific characteristics of the test depot. Any changes in schedules, vehicle types or in operations would likely break the model. This lack of adaptability limits the model's practical use outside of the original scenario. While the model functioned well under ideal conditions, its strict assumptions, lack of slack and reliance on a fixed structure made it difficult to apply in more dynamic contexts. The logic can still be valuable for similar problems, but it requires adjustments to different depot layouts.

5.4 Model benefits

The applied model of k-approach provides quite robust solutions when it finds a feasible solution and the logic behind it solves multiple problems related to bus parking planning. The value of k can be set as high as possible to find the most robust solution. When some bus breaks, there is probably the same bus type available in the allocation plan as it has the maximum of two-block patterns. For this reason, the model reduces the possibility for a bigger amount of mismatches in bus types if available buses do not match what is planned, and dispatching of buses needs to be readjusted on the go. In these scenarios we seek to minimize bus type switches to reduce costs and this model helps to enable that.

The model was proven to be quite fast to recalculate with this size of scenario, which makes it a reasonable solution to use in practice and try different k values. The run time for the whole model was under 1 minute. The problem of this kind could become complex and demanding in calculation time quite fast, but this looks not to be the case with our solution.

Our own addition of designing and adding constraints to the k-position approach is readily adaptable to different depot layouts. It is relatively straightforward to interpret what kind of bus types can be set in specific lanes and defining constraints based on that to allow only some of the patterns for a specific amount of lanes and this way manipulating what kind of patterns the k-position approach gives as an optimal solution. In practice, many depots have this kind of constraints which also makes it hard to directly apply models from literature to practical use. Our way to add these constraints this way addresses this issue and could be implemented also to other models presented in Hamdouni et al. (2007a) and Hamdouni et al. (2006).

To summarize model benefits, the developed model is a good solution to plan bus allocation in a depot if there are not too many different types of buses and the layout of depot is not too complex and all buses leave the depot during the day. If there are multiple feasible solutions for the plan, this model finds the most robust solution quite quickly.

6 Discussion

6.1 Identified good practices to design a robust electric bus depot

During the project, we identified multiple things in depot organizing and bus route planning, which significantly complicated the process of finding robust solutions by utilizing mathematical models. In general, the larger the number of different kinds of bus types, the harder the situation becomes to find good solutions. If it is possible, the number of different bus types could be reduced. Usually, the constraints of used bus types are coming from contracts between a bus company and a city, as there are agreements that a specific color or electric bus should be driving specific routes, and other bus types would add costs for a bus company. As these are coming from contracts, it might be possible to change them by negotiating. All different constraints make the system more complex and harder to create feasible allocation plans.

All limitations or specific conditions, where different buses can be parked and where not, make it less probable to find a solution without rearrangements of buses in a depot. So limiting these conditions if possible, is an important first step when planning the bus allocation. Especially, it would be important that one lane has the same kind of characteristics for each parking slot in it. For example, there would be a charger for each slot in one lane. Adding more parking slots outside which do not have the condition of being filled with the first in first out principle is something that makes the system more relaxed and adds probability to find feasible allocation plans.

The Koiviston Auto's data defines that the same bus drives the whole day the same shift even though it includes charging in the depot in the middle of the day. If these shifts would be divided into two shifts for the day, it would have more feasible solutions if different buses could take care of different parts of shifts in an optimal way. Our model would not directly work in this case as then we would violate the rule that all buses arrive to the depot before any of them leave. In general, this would be a better way to plan the bus usage and shifts.

As already noted, it would be useful to use more electric buses leaving from outside parking slots as these do not need to respect first in first out logic. This would be especially useful when not all buses are leaving the depot during the day. In this case, it would be smart to plan bus types for different shifts that we use lanes from inside depot so that the whole lane is needed. If the needed number of buses is not a multiple of lane length, the remainder number of buses is taken from outside parking slots. This is the only way to make plans where rearrangements are not needed.

6.2 Future directions to continue the work

After literature review, we decided to start using k-position approach as our starting point for our model as it was deemed to be the best solution for the client's wishes about the model. Later in the project, when we started to develop the model for the weekend, the model proved to be inappropriate for situations where the whole bus fleet is not leaving the depot during the day. This is because the model didn't allow rearrangements and only two block patterns. As a future direction for the problem, it may be a good idea to try add features from models with rearrangements Hamdouni et al. (2006) or minimization of type mismatches Hamdouni et al. (2007a) to this model. As these all models are based on similar thinking on lane patterns, it might be possible to combine features from different models into one model. The model from Azema et al. (2024) allowed also longer planning horizon than one night, so it might be also possible to utilize this kind of model to solve the problem of weekend allocation. As the project scope and time was limited, we did not have time to try these.

We also thought about a possibility to build a one singular model for all weekdays, which would return a same bus allocation plan by type for each separate day. A starting point for this model would have been a separate model for each weekday and then all lane variables (represented by X in the k-position approach) would have been restricted by constraints to be the same for every separate weekday. For this specific problem, it would have been possible to find a feasible solution, because there are still quite a few degrees of freedom in parking the buses for each separate day. There would have still been some modeling "tricks" discussed earlier that would have had to have been implemented, e.g. addressing how the "blocking" diesel buses in the first row in columns H, I and J leave during the weekends. Also, not all lanes would be optimized during the weekend: the lanes with only diesel buses would be left out. Overall, we think that while this type of a model could be technically implementable, it is quite burdensome to implement in practice and also very difficult to maintain. This could still be a potential future direction for the work, if the problem can be simplified from what it is now.

7 Conclusions

The first objective of the project was to develop an automated tool to reduce manual labor related to planning the parking and dispatching of buses in the Koiviston Auto Jyväskylä depot. The second objective was that the resulting plans should be more robust against the stochastic arrival times, which would increase the usage of electric buses. This is due to the most common disruption to the plan which is that some bus is quite late to the depot, meaning it can not be parked in its designated spot and if it is an electric bus it might not be able to fully charge during the remainder of the night before its next shift. In these situations an on call vehicle is used to fill in for it and these on call vehicles are exclusively non-electric in our case.

Based on the results, an automated tool is possible to develop on the groundwork done here. The model fell short of fully meeting the client's expectations since it does require notable amount of data preprocessing for it to work in any scenario with any planned bus tours. A notable limitation in our model we noticed is that for poorly designed bus tours, it is not able to produce a parking plan at all. Our extension to the optimization model presented in Hamdouni et al. (2007b) proved to be useful when trying to work with highly specific requirements of real-world bus depots as input to the model.

The model successfully generated robust weekday schedules for parking and dispatching of the buses using a modified k-position approach with specific constraints tailored for the scenario's depot. Key extensions allowed the model to account for non-uniform lanes with respect to the number of spots and type of buses possible to park in them.

References

Azema, M., Desaulniers, G., Pesant, G., and Mendoza, J. (2024). A constraint programming model for the electric bus assignment problem with parking constraints. *Lecture notes in Computer Science*, 14742:17–33.

Bahrami, S. and Roorda, M. (2020). Autonomous vehicle relocation problem in a parking facility. *Transportmetrica A: Transport Science*, 16(3):1604–1627.

Hamdouni, M., Desaulniers, G., and Soumis, F. (2007a). Parking buses in a depot using block patterns: A benders decomposition approach for minimizing type mismatches. *Computers Operations Research*, 34(11):3362–3379.

Hamdouni, M., Soumis, F., and Desaulniers, G. (2007b). Parking buses in a depot with stochastic arrival times. *European Journal of Operations Research*, 183:502–515.

Hamdouni, M., Soumis, F., Desaulniers, G., Odile, M., and van Putten, M. (2006). Dispatching buses in a depot using block patterns. *Transportation Science*, 40(3):364–377.

Koiviston Auto (2025). Koiviston auto official website. Accessed: 3.5.2025.

Koiviston Auto Group (2024). Sustainability report 2023. Internal company document. Accessed: 3.5.2025.

Lajunen, A. (2014). Energy consumption and cost-benefit analysis of hybrid and electric city buses. *Transportation Research*, 38:1–15. Online.

Pennanen, O.-P., Pelo, E., Honkamaa, E., Virtanen, J., and Rühr, A. (2025). JyvaskylaDepotOpt. Accessed: 12.5.2025.

Winter, T. and Zimmermann, U. (2000). Real-time dispatch of trams in storage yards *. *Annals of Operations Research*, 96(1):287–315.

8 Self assessment

8.1 How closely did the actual implementation of the project follow the initial project plan? Were there any major departures and, if so, what?

The scope of the project proved to be very large due to unexpected complexity of the problem. We spent a lot more time reading, discussing and understanding the problem than we initially thought. This naturally led us to deviate from the initial project plan slightly. We chose to narrow down the scope of the project to fit into the time that was allocated to completing it. We completely left out some aspects that were initially on the table such as the interim charging of buses during their shifts. In addition to these simplifications to the problem we had to narrow down our investigation of robustness. Additionally the validation of the results had to be done independently while developing the model and we only briefly managed to go over the results with the client in a short meeting.

We were forced to start the writing of this final report later than originally planned, since we were working on the model until the start of May. Apart from these the initial timeline was roughly followed according to plan in earlier stages of the project. With the narrowing of the scope we did, we completed the project done within the schedule of this course.

8.2 In what regard was the project successful?

The two main objectives of the project were achieved, meaning that we managed to develop an automated tool to produce robust parking and dispatching plans for the depot's buses and these plans proved to be more efficient than manually made ones according to our heuristics and result validation with the client. Koiviston Auto is able to use the tool developed by us to reduce manual labor and develop these efficient plans. We have laid groundwork for them to adapt our tool to other depots with relatively straightforward modifications and they may if they choose to further develop it into a fully automatic tool for them to use requiring next to no manual data preprocessing.

The communication within the team was largely successful. For the first couple of months of the project we managed to roughly stick to our plan of weekly meetings. In these meetings all team members got to voice their opinions, thoughts and findings they had gathered. Having a group chat in Telegram, where we could communicate freely and in fast manner was also crucial for communication and getting help from the other team members. For the last stage of the project we had multiple successful crunch days, where we worked on the technical implementation of the tool together.

Every member got to strengthen their skills in both soft and technical skills. We gained valuable experience in teamwork, public speaking, and problem solving, while also deepening our technical skills in optimization, algorithms, and data processing. Especially we feel like problem solving with qualitative methods was really useful when we were forced to think outside the box for solutions to our problem and also when we were analyzing what traits do good bus tour schedules and bus parking plans have.

8.3 In what regard was it less so?

Unfortunately we did not have enough time for result validation and no time for sensitivity analysis at all. Although in hindsight the latter proved to be a little bit less crucial for our project due to the robust nature of our approach to the problem. Additionally the technical scope of the project proved more ambitious than the available time at our disposal. We started implementing a GUI which was ultimately completely scrapped when the idea of building an integrated app to the client's existing system. Fortunately this idea was scrapped by a joint decision with the client when we realized the underestimated complexity of the problem.

We initially overestimated our capabilities, which led to us wasting time chasing solutions we were not able to produce. Starting out earlier with an ever simpler model than the resulting model was would have been a better approach. From there we could have then expanded until we and the client were satisfied with the results.

8.4 What could have been done better, in hindsight?

From the viewpoint of the client we think the purpose of the project could have been clearer from the start. Our initial impressions of the problem based on the topic presentation varied significantly from the final version of the problem. Also the scope of the problem could have been clearly defined and narrowed in scope for us.

Now from the viewpoint of the teachers and the course. The project plan could have been even more preliminary. This would then allow an even earlier deadline for it and an earlier seminar date for the presentations. We feel like this modification would kick start the projects earlier in the spring allowing more time to be spent in the core work of the projects. Also having the interim report deadline and corresponding presentations earlier would have given more valuable time between it and the very heavy workload bearing final report.