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Study on sensitivity of electric bus systems under simultaneous optimization of charging infrastructure and vehicle schedules

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ABSTRACT

The transition from traditional fuel-based bus transportation towards electric bus systems is regarded as a beacon of hope for emission-free public transport. In this study, we focus on battery electric bus systems, in which charging is possible at a variety of locations distributed at terminal stations over the entire bus network. In such systems, two intertwined planning problems to be considered are charging location planning and electric vehicle scheduling. We account for the interdependent nature of both planning problems by adopting a simultaneous optimization perspective. Acknowledging the existence of parameter uncertainty in such complex planning situations, which is rooted in potential changes of values of several environmental factors, we analyze the solution sensitivity to several of these factors in order to derive methodological guidance for decision makers in public transportation organizations. Based on the formulation of a new mathematical model and the application of a variable neighborhood search metaheuristic, we conduct sensitivity analysis by means of numerical experiments drawing on real-world data. The experiments reveal that it is not possible to identify persistent structures for charging locations by an a priori analysis of the problem instances, so that rather a simultaneous optimization is necessary. Furthermore, the experiments show that the configuration of electric bus systems reacts sensitively to parameter changes.

1. Introduction

Electric buses are regarded as a beacon of hope for emission-free public transport. An electric bus achieves a 19%–32% reduction in CO_2 emission from a life-cycle perspective compared to a diesel bus making the deployment worthwhile (Zhou et al., 2016). The transition from traditional fuel-based bus systems towards electric bus systems is stimulated by the Sustainable Development Goals of the United Nations (UN, 2020) and by several (trans)national regulations. For example, the European Union targets electric vehicle sales shares up to 65% by 2030 for urban buses (European Parliament & Council, 2019). In some countries this is expressed in bans on the purchase of non-electric buses, such as in Norway and the Netherlands from 2025 (Government of Norway, 2016; Government of the Netherlands, 2017). Similar measures also apply outside the EU (see e.g. IEA, 2020). Resulting in growing pressure on public transport companies all over the world not only to replace their diesel buses with electric buses, but also to provide appropriate charging infrastructure.

While the term *electric bus* often refers to both *fuel cell electric buses* as well as *battery electric buses* (BEB), we will focus on the latter type[1] as this technology is strategically favored by the majority of bus operators in Europe (see UITP, 2018). BEB can be further distinguished in respect to their charging concept. In Europe, the *opportunity charging concept* (charging is possible at a variety of locations distributed over the entire bus network) and the *depot charging concept* (charging is possible only at one or several depots) are the most common. In terms of total cost of ownership, opportunity charging is superior to depot charging according to several studies (Jefferies and Göhlich, 2020; Nicolaides et al., 2019; Vilppo and Markkula, 2015) and therefore subject of this work.

Key planning problems to be considered for the widespread introduction of battery electric buses include two broad categories: (i) Setting up the charging infrastructure aims at determining the locations of charging stations to be installed for the electrification of a single bus line (Berthold et al., 2017) or a whole bus network with predefined bus routes (Kunith et al., 2017; Xylia et al., 2017a); thereby, it represents a long-term planning problem. (ii) Scheduling electric buses, respecting their limited range and charging times, addresses the problem of assigning electric buses to cover a given set of timetabled trips, with the

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[1] Hence, the terms *electric bus* and *battery electric bus* are used synonymously in this paper.

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network of charging stations already given as input (Wen et al., 2016; Adler and Mirchandani, 2017). This planning problem is of operational nature and has been coined the Electric Vehicle Scheduling Problem (EVSP) (Reuer et al., 2015).

Electric vehicle scheduling in practice is usually approached given an electric infrastructure as result of preceding infrastructure planning and implementation, establishing an overall sequential planning process of BEB transportation systems. However, dependencies between both planning problems also exist in the opposite direction when planning the electric infrastructure benefits from anticipating scheduling requirements in order to enable cost-efficient schedule operations. The resulting interdependent nature of both planning problems call for a simultaneous optimization of electric charging infrastructure and electric vehicle schedules, which allows public transport bus operators to achieve lower cost and more rider- and customer-friendly schedules than achievable through a sequential planning process (Olsen and Kliewer, 2020a). Aiming at tapping the potential of a simultaneous planning process, some scholars (e.g. Rogge et al., 2018) provide methods that consider the scheduling of battery buses and the optimization of charging infrastructure in a joint process.

The above-mentioned planning problems need to account for a variety of environmental factors. These factors refer to the technological configuration, including battery capacity size and charging power of charging stations (Göhlich et al., 2018) as well as the levels of energy consumption of electric buses (An, 2020; Vepsäläinen et al., 2018), the infrastructure in terms of whether mixed or fully electrified fleets are considered, the charging process in terms of whether only full or also partial charging is allowed, and economic parameters, such as investment costs for electric buses and charging stations. Accounting for parameter uncertainty due to changes of the environmental factors, some optimization approaches – either targeting finding optimal solutions (or identifying bounds), or focusing on (meta-/mat-)heuristic approaches – have applied sensitivity analysis, which is a valuable methodology to quantify relationships between changes of objective values and changes of environmental parameter values. In considering such uncertainties while planning the charging infrastructure, which is characterized by the fact that decisions once made cannot be revised during the gradual expansion of charging infrastructure, it is important to incorporate persistent structures. The term *persistent structure* denotes a kernel set of charging locations which enables feasible and sufficiently low-cost bus operations independent of variations in environmental factors.

To our best knowledge, prior research has not accounted for both the need for simultaneous planning of the electric charging infrastructure and electric vehicle schedules to realize a BEB transportation system and the need to account for parameter uncertainty by means of sensitivity analysis. Addressing this research gap, the objective of our work is the application of a method which simultaneously optimizes both charging locations and vehicle schedules, and the computational analysis of gained results across parameter settings for various problem instances in order to answer the following question: *To what extent does the application of a metaheuristic solution approach to the joint problems of charging location planning and electric vehicle scheduling allow finding persistent structures within the charging infrastructure?* Insights in this issue are valuable to guide future methodological research on obtaining solution robustness.

In order to answer our research question, we suggest a new mathematical model for the simultaneous optimization of charging locations and vehicle schedules of electric bus systems. Accounting for the computational complexity of solving large-scale instances, we implement a Variable Neighborhood Search (VNS) metaheuristic, which has been effective in a variety of application areas (Hansen et al., 2010, 2019; Hansen and Mladenović, 2001). Drawing on several real-world instances and empirical data, we computationally apply VNS on various problem instances of different size with different topological characteristics. Our computational experiments focus on the analysis of solution robustness against changes of three environmental factors: i) the ratio between investment costs per electric bus and those per charging station, ii) technological variations concerning size of battery capacity and power of charging stations and iii) varying energy consumption due to fluctuations in temperature and traffic volume.

The remainder of this paper is organized as follows. Section 2 presents literature related to the optimization of charging locations and vehicle schedules for electric bus systems. In Section 3 we provide the problem specification and suggest a mixed-integer linear problem formulation. In Section 3.3, we propose our solution method using a problem-specific metaheuristic. In Section 4, we describe the setting and the results of our computational experiments, and we discuss the findings. Section 5 concludes our work with a summary of our study and an outlook on future research.

2. State of the art: Charging location planning and electric vehicle scheduling

Research related to the problem considered in this paper can be distinguished along the fields of *Charging Location Planning* for urban and suburban electric bus systems, *Electric Vehicle Scheduling* in public transport, and approaches addressing both problems *simultaneously*. Research related to issues of Total Cost of Ownership, the Vehicle Routing Problem, private electric vehicles, in-motion charging technology, or charging scheduling are out of scope of our review. We further limit our literature review to articles which suggest optimization approaches, such as mathematical problem formulations or problem-specific solution methods.

We classify papers along the following attributes as they were identified in the introduction (compare Table 1). *Technological Configuration* refers to the consideration of the power of the charging stations (P) or the battery capacity of the electric buses (B) as decision variables. The attribute *Mixed Fleet* is assigned to an approach if the considered bus fleet consists of both electric buses and fuel-based buses, resulting in the need to assign one of these bus types to each bus route. *Partial Charging* refers to the possibility that buses are not necessarily fully charged during a charging process, but may be charged to a state of charge (SoC) that is below the battery capacity. Moreover, we label those studies which perform a *Sensitivity Analysis* in order to account for a change of energy consumption (E), the power of charging stations (P), the battery capacity of electric buses (B), or the cost of buses, charging stations or energy (C). Finally, studies where optimal solutions or the gap to the optimal solution are obtained are labeled as *Exact Solution*.

The charging location planning for urban electric bus systems is, in contrast to private electric vehicles, characterized by predetermined and fixed routes of the vehicles. All approaches dealing with the use of this problem address the primary goal of determining the locations of charging stations to be installed to enable the operation of a given timetable by electric buses, at least partially. Xylia et al. (2017b), Wei et al. (2018) and Kovalyov et al. (2020) consider gradual electrification of a bus system and therefore assume a mixed fleet. The models suggested in these studies are used to select specific routes that are particularly suitable to be operated by electric buses and that, therefore, need to be equipped with charging infrastructure. In contrast, many other approaches exist where the charging infrastructure is determined so that all pre-selected routes can be served by a fully electrified bus fleet (Chen et al., 2013; Berthold et al., 2017; Kunith et al., 2017; Wang et al., 2017; Liu et al., 2018; Cheng et al., 2019; Lin et al., 2019; He et al., 2019; An, 2020). Most of these approaches also incorporate partial charging.

The EVSP in public transport is a new variant of the traditional VSP, which has been well studied in the OR literature (Bunte and Kliewer, 2009). The EVSP addresses the problem of assigning electric buses to cover a given set of timetabled trips, with the network of charging stations already given as input. Apart from a few exceptions where a mixed fleet is considered (Paul and Yamada, 2014; Sassi and

Table 1
Classification of literature studies

	Reference	Technological Config.	Mixed Fleet	Partial Charging	Sensitivity Analysis	Exact Solution
Charging Location Planning	Chen et al. (2013)	P,B		•		•
	Berthold et al. (2017)			•	E	•
	Kunith et al. (2017)	B		•	E,P	•
	Xylia et al. (2017b)		•	•	P	•
	Wang et al. (2017)			•	B,C	•
	Wei et al. (2018)		•			•
	Liu et al. (2018)	P,B		•	E	•
	Cheng et al. (2019)			•	E,C	•
	Lin et al. (2019)					•
	He et al. (2019)	P,B		•	C	•
	Kovalyov et al. (2020)	P,B	•			
	An (2020)			∘	E	•
Electric Vehicle Scheduling	Wang and Shen (2007)					
	Chao and Xiaohong (2013)					
	Li (2014)					•
	Paul and Yamada (2014)		•	•	P	
	Wen et al. (2016)			•	P,B	
	Ke et al. (2016)	B				
	Adler and Mirchandani (2017)					•
	Sassi and Oulamara (2017)		•	•		•
	van Kooten Niekerk et al. (2017)			•		•
	Jiang et al. (2018)			•	C	
	Tang et al. (2019)				P,B	•
	Guo et al. (2019)			∘		•
	Messaoudi and Oulamara (2019)					
	Olsen et al. (2020)		•		P	•
	Janovec and Kohání (2020)			•		•
	Rinaldi et al. (2020)		•			•
	Liu and Ceder (2020)			•		
	Zhou et al. (2020)		•	∘		
Simultaneous Approach	Rogge et al. (2018)	B		•		
	Li et al. (2019)		•		B,C	•
	Häll et al. (2019)				B	•
	Yao et al. (2020)	B			P,B	
	Lu et al. (2021)		•			

Legend: E - energy consumption; P - power of charging stations; B - battery capacity of electric buses; C - costs for buses or charging stations or energy; • - The respective attribute is fulfilled; ∘ - From reading the paper, we could not figure out whether partial charging is allowed

Oulamara, 2017; Olsen et al., 2020; Rinaldi et al., 2020; Zhou et al., 2020), most studies dealing with this problem assume the bus fleet to be fully electrified. While in early papers dealing with the EVSP (Wang and Shen, 2007; Chao and Xiaohong, 2013; Li, 2014) as well as in some more recently published papers (Adler and Mirchandani, 2017; Ke et al., 2016; Tang et al., 2019; Messaoudi and Oulamara, 2019), buses are required to get fully charged once a charging process has launched, in recent literature partial charging is possible, allowing for a more efficient use of electric buses (Wen et al., 2016; van Kooten Niekerk et al., 2017; Jiang et al., 2018; Janovec and Kohání, 2020; Liu and Ceder, 2020). Among the fully electrified approaches, only in Guo et al. (2019) it is not apparent whether partial charging is allowed.

In the literature, only few approaches exist which consider both the optimization of charging infrastructure and the scheduling of battery buses simultaneously, acknowledging interdependencies between the two partial problems. In Li et al. (2019) and Lu et al. (2021), timetabled trips are assigned to a mixed fleet of electric buses and fuel-based buses, and the problem of locating refueling stations at terminal stops (Li et al., 2019) or depots (Lu et al., 2021) is addressed simultaneously. Methodologies for the cost-optimized planning of fully electrified bus fleets and their corresponding charging infrastructure are presented by Rogge et al. (2018) and Yao et al. (2020) only for the depot charging concept and by Häll et al. (2019) also for the opportunity charging concept. However, none of these approaches cover the complete charging location planning in its original sense as either the charging locations are fixed by only considering depot charging or the number of charging stations is predetermined (cf. Häll et al., 2019).

The classification of studies along problem types and the above-mentioned attributes is summarized in Table 1. We put emphasis to two specific characteristics of the body of literature: First, only very few studies have considered the interdependencies between charging location planning and electric vehicle scheduling through simultaneous studies. Second and from a methodological perspective, sensitivity analysis has become common practice, accounting for the nature of uncertainty of several exogenous factors. Drawing on both observations, we contribute to the literature by suggesting a model that simultaneously addresses charging location planning and electric vehicle scheduling subject to the opportunity of partial charging and subject to a fully electrified battery bus fleet with fast charging technology. We refer to the considered problem as the “Charging Location and Electric Vehicle Scheduling Problem” (CLEVSP).

3. Mathematical model and VNS-based solution approach for the CLEVSP

In this section, we provide the specification of our planning problem CLEVSP and suggest a new mathematical model for this problem. We also describe a VNS-based metaheuristic, which we use in our numerical experiments to solve real-world CLEVSP instances.

3.1. Problem specification

We consider the problem CLEVSP, which simultaneously optimizes the charging infrastructure and the vehicle schedules of an opportunity charging electric bus system, assuming a fully electrified homogeneous bus fleet situated in one depot. The objective is to minimize the sum of i) investment costs into charging infrastructure and electric buses, and (ii) operational costs resulting from implementing vehicle schedules, while ensuring the operation of a given timetable.

A *vehicle schedule* is defined as the assignment of timetabled trips to vehicles, represented through a list of bus rotations. A *bus rotation* refers to a sequence of vehicle activities, including service trips, deadhead trips, waiting times, and charging processes of vehicles. Based on a given timetable, a *service trip* transports passengers along the route of a bus line between two terminal stops, from a departure stop to an arrival stop, and is specified by a departure and arrival time. We refer to all other trips as *deadhead trip*, which are required to connect two service trips or the depot with a service trip. The characteristics of a deadhead trip, including distance and duration, depend on the pair of terminal stops that are connected. Deadhead trips as well as waiting times are not given in advance but result from the combination of service trips. This logic also applies to charging processes, which are required when a bus needs to recharge in order to ensure its battery capacity will not fall below a required level of battery capacity during subsequent trips. A *charging process* is characterized by the location where it takes place and its duration. Possible locations for charging are the depot and all terminal stops specified in the timetable, provided they are equipped with charging capabilities. The duration of a charging process depends on the waiting time, the energy levels before and after charging (which in our case does not need to equal the battery capacity since we allow partial charging) and the charging power available.

We assume that the depot has charging capabilities so that buses always leave the depot with a fully charged battery. Since we consider a homogeneous fleet, all buses have the same battery capacity and thus the same range. The average energy consumption differs between service trips and deadhead trips, due to different speeds and passenger loads. Moreover, we assume identical charging power for all charging stations of the charging infrastructure as well as linear charging power functions as approximation for often nonlinear charging times in practice (Olsen and Kliewer, 2020b). We further suppose that each terminal stop has access to the power grid and is thus a candidate for a charging station.

Based on the above assumptions, the task is to jointly determine an electric vehicle schedule (in terms of bus rotations), a bus fleet (in terms of the numbers of electric buses required), and a charging infrastructure (in terms of potential locations of charging stations and their total number) which are cost-minimal with regard to the sum of investment costs into charging infrastructure and electric buses, and operational costs resulting from vehicle schedules, subject to the above-mentioned constraints.

Fig. 1 illustrates a sample solution for a problem instance with four service trips (ST_1, …, ST_4) represented as nodes; deadhead trips are indicated through directed edges. The depicted solution includes a vehicle schedule consisting of two rotations ([Depot, ST_1, ST_3, Depot] and [Depot, ST_2, ST_4, Depot]), which require one electric bus each. For two service trips ST_2 and ST_3, the arrival and departure stops and the departure and arrival times are shown in the right part of Fig. 1. For example, ST_2 leaves terminal stop A at 9:30 and reaches terminal stop B at 10:20. Since terminal stop B has a charging station, the bus serving ST_2 can charge its battery at this stop B immediately after ST_2. Note that the arrival stop of ST_2 and the departure stop of ST_3 represent the same location (terminal stop B). As a result, charging processes for both buses can be executed at the same terminal stop B, resulting in the need to equip only one terminal stop with charging capabilities.

3.2. Mathematical model

The mathematical problem formulation is based on a directed graph as it is shown for a sample solution in Fig. 1; its construction is based on the ideas of Freling and Paixão (1995). The input for the model is a set of service trips $I = \{1, \dots, n\}$, which is ordered by increasing departure time. Then, the directed graph can be represented as $G = (V, A)$, with nodes $V = I \cup \{n+1\}$ and edges $A = \{(i, j)\} \cup (n{+}1, i) \cup (i, n{+}1)$. Here, the depot corresponds to the node $n+1$, all other nodes represent service trips. A directed edge $(i, j) \in A$ indicates a deadhead trip, including *depot trips* which connect the depot i with a service trip j or a service trip i with the depot j, and *connecting trips* which connect two service trips i and j by requiring a bus either to physically move between two terminal stops or to remain at a single terminal stop when this stop is both the arrival stop of service trip i and the departure stop of service trip j (virtual connecting trip). Set $A' \subset A$ defines all connecting trips. For each connecting trip $(i, j) \in A'$, the following inequation holds:

$$\beta_i + \gamma_{i,j} + \delta_{i,j} \leq \alpha_j \tag{1}$$

where α_i and β_i denote the departure time and the arrival time of a service trip i, respectively, and $\gamma_{i,j}$ refers to the duration of and $\delta_{i,j}$ to the idle time before/after the deadhead trip $(i, j) \in A'$.

Furthermore, the set S indicates all departure and arrival stops of service trips that are eligible for the installation of a charging station, which are synonymously referred to as stops in the following. The sets O_s and D_s are used for the assignment between departure and arrival stops and service trips. While O_s contains the service trips starting at stop s, the service trips ending at stop s are included in D_s. The set B comprises the number of all available electric buses. An overview of the notation for sets, variables and parameters used in the model can be found in Appendix A.

We use the following decision variables: Binary variables $x_{i,j,b}$ with $(i, j) \in A$, are used to indicate (with value 1) whether service trip j (or the depot) directly follows service trip i (or the depot) in a bus rotation served by bus b. These variables determine the sequence of service trips that are operated within a bus rotation. Each bus rotation starts and ends with a depot trip, contained in the set A as $(n{+}1, i)$ or $(i, n{+}1)$. The planning of other vehicle activities within the sequence of a rotation is done by assigning the activity, for example a charging process, to the departure or arrival of a service trip. Hence, binary variables y_i^{arr} and y_i^{dep} are used to map charging processes to the departure and arrival stops of service trips. For example, $y_i^{arr} = 1$ implies that a charging process takes place at the arrival stop of the service trip i. Otherwise,

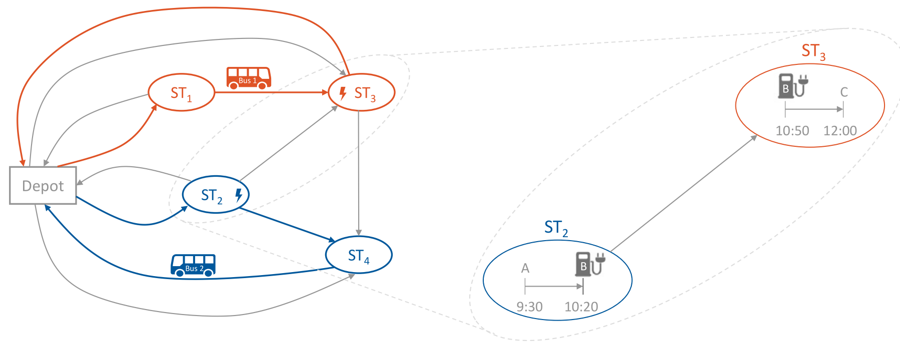


Fig. 1. Sample Solution for a problem with four service trips.

the variable is assigned value 0. The analogous logic applies to y_i^{dep} with reference to the departure stop. Finally, the binary variable z_s is used to determine whether a charging station must be set up at stop s ($z_s = 1$) or not ($z_s = 0$). The continuous variables $t_{i,b}^{arr}$ and $t_{i,b}^{dep}$ specify the charging time in minutes that the bus b needs at the arrival or departure stop of the service trip i, respectively. The continuous variables $l_{i,b}^{arr}$ and $l_{i,b}^{dep}$ refer to the energy levels of a bus b before and after the operation of service trip i. The energy a bus holds right before it executes service trip i is equal to $l_{i,b}^{dep}$ given in kilowatt hour, including the charged energy in a possibly preceding charging process (if $y_i^{dep} = 1$). Similarly, $l_{i,b}^{arr}$ represents the energy level of the bus b at the arrival stop of the service trip i, which if a charging process takes place after the service trip i (marked by $y_i^{arr} = 1$) already takes into account its energy increase.

The overall mathematical model is given below.

$$\min \sum_{b\in B}\sum_{(i,j)\in A}(c_{i,j}^{fix} + c_{i,j}^{hour} + c_{i,j}^{km})x_{i,j,b} + \sum_{s\in S} c_s z_s \tag{2}$$

Subject to:

$$\sum_{\{j:(i,j)\in A\}} x_{i,j,b} - \sum_{\{k:(k,i)\in A\}} x_{k,i,b} = 0 \qquad \forall\, i \in I;\ \forall\, b \in B \tag{3}$$

$$\sum_{b\in B}\sum_{(i,j)\in A} x_{i,j,b} = 1 \qquad \forall\, i \in I \tag{4}$$

$$\sum_{i\in I} x_{n+1,i,b} \le 1 \qquad \forall\, b \in B \tag{5}$$

$$l_{i,b}^{arr} = l_{i,b}^{dep} - \sum_{\{j:(i,j)\in A\}} n_i x_{i,j,b} + \frac{p}{60} t_{i,b}^{arr} \qquad \forall\, i \in I;\ \forall\, b \in B \tag{6}$$

$$l_{j,b}^{dep} \ge l_{i,b}^{arr} - n_{i,j}x_{i,j,b} + \frac{p}{60} t_{j,b}^{dep} - M\left(1 - x_{i,j,b}\right) \quad \forall\,(i,j) \in A;\ \forall\, b \in B \tag{7}$$

$$l_{j,b}^{dep} \le l_{i,b}^{arr} - n_{i,j}x_{i,j,b} + \frac{p}{60} t_{j,b}^{dep} + M\left(1 - x_{i,j,b}\right) \quad \forall\,(i,j) \in A;\ \forall\, b \in B \tag{8}$$

$$l_{i,b}^{dep} \le cap \sum_{\{k:(k,i)\in A\}} x_{k,i,b} \qquad \forall\, i \in I;\ \forall\, b \in B \tag{9}$$

$$l_{i,b}^{arr} \le cap \sum_{\{j:(i,j)\in A\}} x_{i,j,b} \qquad \forall\, i \in I;\ \forall\, b \in B \tag{10}$$

$$l_{n+1,b}^{arr} = cap \sum_{i} x_{n+1,i,b} \qquad \forall\, b \in B \tag{11}$$

$$l_{i,b}^{dep} - \sum_{\{k:(k,i)\in A\}} n_i x_{k,i,b} \ge d \sum_{\{k:(k,i)\in A\}} x_{k,i,b} \qquad \forall\, i \in I;\ \forall\, b \in B \tag{12}$$

$$l_{i,b}^{arr} - \sum_{\{j:(i,j)\in A\}} n_{i,j} x_{i,j,b} \ge d \sum_{\{j:(i,j)\in A\}} x_{i,j,b} \qquad \forall\, i \in I;\ \forall\, b \in B \tag{13}$$

$$l_{n+1,b}^{dep} \ge d \sum_{i\in I} x_{i,n+1,b} \qquad \forall\, b \in B \tag{14}$$

$$t_{i,b}^{dep} \le \sum_{\{k:(k,i)\in A\}} \delta_{k,i} x_{k,i,b} \qquad \forall\, i \in I;\ \forall\, b \in B \tag{15}$$

$$t_{i,b}^{arr} \le \sum_{\{j:(i,j)\in A\}} \delta_{i,j} x_{i,j,b} \qquad \forall\, i \in I;\ \forall\, b \in B \tag{16}$$

$$t_{i,b}^{arr} + t_{j,b}^{dep} \le \delta_{i,j} x_{i,j,b} + M\left(1 - x_{i,j,b}\right) \qquad \forall\,(i,j) \in A';\ \forall\, b \in B \tag{17}$$

$$\sum_{i\in I: i\in O_s} y_i^{dep} + \sum_{i\in I: i\in D_s} y_i^{arr} \le M z_s \qquad \forall\, s \in S \tag{18}$$

$$t_{i,b}^{dep} \le M y_i^{dep} \qquad \forall\, i \in I;\ \forall\, b \in B \tag{19}$$

$$t_{i,b}^{arr} \le M y_i^{arr} \qquad \forall\, i \in I;\ \forall\, b \in B \tag{20}$$

The objective function (2) is composed of two parts: the costs resulting from the vehicle schedule and the costs for charging infrastructure. The number of rotations in the vehicle schedule determines the number of buses needed to serve the given timetable. For a given solution, the number of edges leaving the depot is equal to the number of bus rotations in the vehicle schedule. Therefore, the investment costs per electric bus $c_{i,j}^{fix}$ are assigned to the pull-out depot trip $(n+1, i) \in A$. In addition, each deadhead trip incurs personnel costs $c_{i,j}^{hour}$ per hour of operation and energy consumption costs $c_{i,j}^{km}$ per kilometer driven. The personnel and energy costs for service trips are not considered in the objective function since they are always the same for a given instance. Fixed investment costs per charging station c_s are caused by the installation of charging technology at terminal stops and add up over the entire bus network to the total costs for charging infrastructure.

Note that investment costs are by orders of magnitude higher than operational costs. Possible cost differences between two feasible solutions with different infrastructure and fleet make-up will be greater than cost differences because of, for example idle time reductions. As a result, the trade-off on the long-term level between the number of vehicles and the number of charging stations will be treated with higher priority than the trade-off on the operational level between idle time, charging time, and deadhead time and consumption.

The first three constraints of the model address vehicle scheduling requirements. Eqs. (3) and (4) guarantee that each service trip is assigned to exactly one bus rotation. The explicit assignment of a bus to exactly one rotation is guaranteed by constraint (5). Each vehicle can leave the depot only once to start a rotation.

Constraints (6) to (8) serve to maintain the energy balance for the entire vehicle schedule. Constraint (6) addresses the energy balance for a service trip. It ensures that the energy level $l_{i,b}^{arr}$ of the bus b at the destination of the service trip i is equal to the energy level $l_{i,b}^{dep}$ at the origin of the service trip minus the energy consumption n_i during the service trip i plus the energy charged at the destination of the service trip (charging power p of the charging station multiplied by the charging time $t_{i,b}^{arr}$). The same principle applies to constraints (7) and (8), which address the energy balance during a deadhead trip $(i,j) \in A$ (including depot trips and connecting trips).

The charging processes must be limited by an upper bound for the energy level. Constraints (9) and (10) limit the maximum energy level of each bus to the specified battery capacity cap. The energy level variables $l_{i,b}^{dep}$ and $l_{i,b}^{arr}$ get the value zero when a bus b does not serve the considered service trip i. Eq. (11) guarantees that each bus leaves the depot with a fully charged battery. Note that the variable $l_{n+1,b}^{arr}$ represents the energy level of the bus b at the beginning of its rotation.

The lower bound for the discharge of the battery d, defined as an absolute safety level during operation, is specified in formula (12) for service trips, in formula (13) for connecting trips and in constraint (14) for depot trips. By using the binary variable $x_{i,j,b}$ on both sides of the inequality, the energy level gets the value zero when a bus does not serve the respective trip. Constraint (14) ensures that buses are required to arrive at the depot with at least a minimum level of energy.

The duration of a charging process at a terminal stop must not exceed the idle time of the bus spent at this stop. While constraint (15) ensures this for all departure stops of the service trips, constraint (16) refers to all arrival stops of the service trips. If charging processes take place before and after a connecting trip $(i,j) \in A'$ the time summed up for both charging processes may not exceed the actual idle time $\delta_{i,j}$ of a bus b. This is ensured by constraint (17)

The assignment of the departure and arrival stops of service trips to terminal stops is considered in constraint (18) using sets O_s and D_s. Only if a charging station is installed at terminal stop s ($z_s = 1$), charging processes can occur there. A distinction is made between charging processes y_i^{dep} at the departure stop of the service trip i and charging processes y_i^{arr} at the arrival stop of the service trip i.

Finally, constraints (19) and (20) ensure that charging times greater than zero can occur only at those departure and arrival stops of the service trips where a charging station is installed.

The size of the presented model in terms of number of decision variables as well as number of constraints depends mainly on the size of the set A representing all possible deadhead trips resulting from feasible combinations of given service trips in set I. The number of deadhead trips $|A|$ grows quadratically as a function of the number of service trips n (with $n = |I|$). Since decision variables $x_{i,j,b}$ as well as constraints (7) and (8) are defined over the set A, the numbers of variables and constraints both grow asymptotically quadratically in n (i.e., $O(n^2)$).

3.3. VNS-based solution approach

Our problem CLEVSP is a generalization of the "Alternative-Fuel Vehicle Scheduling Problem" (AF-VSP, see Adler (2014)), which is equivalent to the EVSP. The generalization is rooted in the additional problem of finding locations for charging stations. As any instance of the AF-VSP can be reduced to an instance of CLEVSP straightforward in polynomial time and the AF-VSP, like all VSP with path-length constraints, has proven to be NP-hard (Bodin and Golden, 1981), CLEVSP is NP-hard, too. Accounting for this computational complexity, we propose a Variable Neighborhood Search (VNS) metaheuristic in this section. Metaheuristics based on VNS have been successfully applied to real-world combinatorial optimization problems in a variety of application areas (cf. Hansen et al., 2010, 2019; Hansen and Mladenović, 2001).

We draw our solution method upon the approach of Olsen and Kliewer (2020a). It consists of two consecutive algorithms: a construction algorithm for generating initial solutions based on the savings algorithm (Clarke and Wright, 1964), and an improvement algorithm applying VNS (Mladenović and Hansen, 1997).

In both algorithms, ensuring feasible rotations is of particular importance. Thus, we first describe a procedure for achieving feasibility before proceeding with a description of the algorithms.

3.3.1. Feasibility procedure

The feasibility procedure serves two important functions: i) Checking whether vehicle rotations are valid in terms of the model constraints presented in Section 3 referring to time and energy. ii) Returning a set of charging procedures and charging stations to be installed, if necessary, to make rotations feasible which cannot be executed with the energy of one battery load. Iterating over the sequence of successive service and deadhead trips, the feasibility procedure, which is based on recursion, checks whether and when the SoC falls below the specified minimum energy level. In case of a shortfall, all terminal stops of previous service trips and the spent waiting times there are screened backwards for the possibility to insert charging processes. All determined charging possibilities are ordered by decreasing *utilization* and the *incident* of the foreseen terminal stop, selecting the first, in order to shift charging procedures from less to more highly frequented charging stations and reduce the number of charging stations. In the case that no charging possibility can be identified, the procedure returns “infeasibility” for the corresponding bus rotation.

3.3.2. Construction algorithm

Starting from bus rotations each containing one service trip, the savings algorithm iteratively merges two rotations into a single one to achieve cost savings, terminating when no further cost-reducing mergings are possible. Merging of two bus rotations occurs if it results in a new feasible bus rotation and the cost savings generated are the highest calculated for all possible combinations of rotations in the current iteration. Feasibility of a bus rotation is fulfilled by satisfying the constraints regarding time and energy mentioned in Section 3. Cost savings refer to the aggregate of savings of fixed costs for vehicles and charging stations as well as operational costs saved by merging rotations.

3.3.3. Improvement algorithm

The improvement algorithm aims at finding a sequence of new solutions with decreasing objective values. The applied VNS method relies on both stochastic and deterministic changes of neighborhoods. In our case, the bus rotations within the vehicle schedule are selected for the definition of a neighborhood N_k, where size $k \in \mathbb{N}$ defines the number of selected bus rotations which are modified. The maximum neighborhood size is given by $k_{max} \in \mathbb{N}$. Starting point of each iteration of the improvement algorithm is a solution that consists of a vehicle schedule specified by bus rotations R, charging stations C and an objective function value that is currently the lowest one found. The incumbent solution is modified in a perturbation phase and a subsequent local search. The application of the method SHAKE implements the perturbation phase where a random recombination of two bus rotations of the defined neighborhood is generated (l. 5 in Algorithm 1). During the local search, the method BESTIMPROVEMENT aims at improving the randomized solution by applying two different neighborhood operators (l. 6 in Algorithm 1). In the next step, the objective function values of the improved and the incumbent solution are compared (l. 7 in Algorithm 1). If the improved solution is better than the incumbent, the method NEIGHBORHOODCHANGE accepts it and changes the neighborhood to the smallest possible size; otherwise the size of the neighborhood is increased. The improvement algorithm terminates when a predefined computation time is exceeded. Algorithm 1 provides an overview of the VNS.

Algorithm 1 Improvement algorithm based on VNS

Input: bus rotations R, charging stations C, t_{max}, k_{max}
Output: bus rotations R, charging stations C

1: $t \leftarrow 0$
2: **while** $t < t_{max}$ **do**
3: $\quad k \leftarrow 1$;
4: $\quad$ **while** $k \le k_{max}$ **do**
5: $\quad\quad (R', C') \leftarrow \mathtt{SHAKE}(R, C, k)$;
6: $\quad\quad (R'', C'') \leftarrow \mathtt{BESTIMPROVEMENT}(R', C', k)$;
7: $\quad\quad (R, C, k) \leftarrow \mathtt{NEIGHBORHOODCHANGE}((R, C), (R'', C''), k)$;
8: $\quad$ **end while**
9: $\quad t \leftarrow CPUTIME()$;
10: **end while**
11: **return** (R, C);

In the remainder of this section, we describe the aforementioned two neighborhood operators as they are used in the method BESTIMPROVEMENT.

2-Opt operator. In order to find improving solutions referring to the VSP facet of the problem, we use a modified r-Opt operator. r-Opt is a type of local search operator commonly used for solving traveling salesman problems or vehicle routing problems. In essence, r-Opt operations replace a set of r basis edges with r non-basis edges. In our specification of the operator, replacements result in solutions where basis edges are part of two different vehicle rotations. In this approach, we set the number of edges r to 2, following a recommendation of Olsen and Kliewer (2020a)). The solution resulting from a replacement is only accepted if it yields a significant improvement of the current local-best objective function value. The improvement is measured by means of the prospect saving, which must be strictly positive and non-marginal to be significant. Since potential reductions of charging system costs are explicitly considered in this operator, it tends to prefer solutions with fewer numbers of installed charging stations.

Service trip translocation. The service trip translocation operator is an adapted node translocation procedure. In contrast to the aforementioned 2-Opt approach, this operator modifies the vehicle schedule by removing service trip nodes from their current vehicle rotation and inserting these into an other rotation. This operator is used for consolidation of vehicle schedules. Thus, trips can only be translocated from shorter towards longer vehicle rotations. As a result, the operator primarily helps to reduce the number of vehicles and the amount of idle time between service trips.

4. Parameter sensitivity study

In this section we present a method to identify persistent structure within the charging locations for an electrified bus transport system (cf. Section 1). To this end, we demonstrate how sensitivity analyses on a multitude of feasible solutions to the CLEVSP can be conducted and interpreted, so as to draw managerial implications and help with the long-term planning of charging infrastructures.

In the following, we formulate hypotheses regarding persistent location structures and test them by analyzing two important features: The **incidence** (whether a stop was equipped with a charging system) and the **utilization** (the number of charging processes at a stop).

Hypothesis 1. Persistent structures within the charging infrastructure can be identified by means of a priori analysis of the problem instances. Topological properties (i.e. the centrality with respect to the distance to all other stops) and timetable-related properties (i.e. the number of arrivals and departures) are predictors for the charging stations incidence and utilization.

Hypothesis 2. The most important input parameters forming the individual configurations have an impact on the composition of the charging infrastructure. Charging system incidence and utilization are subject to the combination of parameter values as well as to selected subsets of these parameters.

4.1. Experiments design

To perform the sensitivity analysis and to check the hypotheses formulated above, we analyze problem solutions, created by simultaneously solving the CLEVSP considering all combinations of plausible values for relevant technological and monetary domain parameters. Table 2 gives an overview of parameter values.

Technological parameters. For this study, we have focused on varying three central parameters, which restrict the driving range of a BEB significantly: Battery capacity, charging power at installed charging systems and the energy consumption per kilometer. These parameters have obvious implications on how resulting solutions are constituted. A higher battery capacity allows for longer runs without recharging, whereas an increase in charging power leads to lower charging times and, thus, increases the number of feasible service trip combinations with respect to planned arrival, dead run, and departure times. Varying

Table 2
Parameter settings for scenarios.

Category	Parameter	Specification		
Investment cost	Bus acquisition cost (in MU)	400.000	600.000	800.000
	Charging system cost (in MU)	300.000	400.000	500.000
Technological properties	Service trip consumption (in kWh/km)	1.5	2.25	3
	Deadhead consumption (in kWh/km)	1	1.5	2
	Battery capacity (in kWh)	200	300	500
	Charging power (in kW)	150	300	600
Operational cost	Energy price (in MU/kWh)	0.1		
	Personnel cost (in MU/h)	20		

the energy consumption changes the overall range limitation. With an increased energy consumption vehicles will have to be charged more frequently and the number of feasible service trip combinations decreases. The assumed capacities approximate currently realistic (200kWh), future increased (300kWh) and very optimistic (500kWh) values. Charging system characteristics equal a panthograph charging system, as currently available on the market.[2] With regard to the energy consumption, service trips with passenger load and dead run trips with curb-weight must be considered differently. Thus, we use two parameters, deadhead consumption vs. service trip consumption, where the latter is assumed to be higher than the former. Raab et al. (2019) calculate three scenarios for the consumption per km of different vehicle types for peak and off-peak times, yet without any distinction between service trips and deadhead trips. As detailed by the authors, consumption estimates are subject to many factors, including heating and air-conditioning. Thus, we approximate realistic values for assumed worst, mean, and best case scenarios, in accordance to Raab et al..‘

Economic parameters. These consist of the two most important cost factors: Bus acquisition cost as the investment cost for procuring a battery electric bus and charging system costs reflecting the costs for the installation of a charging system.[3] We chose market values as detailed in Göhlich et al. (2018) corroborated by knowledge from the practical application. Note that for this study, differences in depreciation are implicitly accounted for in the proportion of charging system costs and bus acquisition costs. Accordingly, values for the respective parameters were chosen to reflect that electric buses exhibit higher depreciation. Moreover, a constant energy price based on European energy prices for businesses (cf. eurostat - European Commission, 2021) is assumed. Similarly, personnel costs are based on an average value for personnel costs for bus drivers in Germany (cf. Bundesagentur für Arbeit, 2019).

Overall, we combine all possible parameter values — consumption (service trip and deadhead consumption are conjointly varied), battery capacity, charging power, bus investment and charging system costs (s. Table 2). Each of the five parameters can have one of three values, which leads to a total of $3^5 = 243$ variations.

Problem instances. We perform the sensitivity analysis as outlined above for three real-world problem instances derived from public bus transport networks and timetables for different cities in Germany.[4] Table 3 gives an overview of the respective characteristics, such as the number of terminal stations as well as the number of service trips in the

[2] https://new.abb.com/ev-charging/products/pantograph-down accessed on June 15, 2021.

[3] Costs include those related to acquisition and installation. The cost for the installation of a converter and outlet/pantograph are not modeled explicitly.

[4] Overall, we calculate three times all 243 variations.

Table 3
Problem instance description.

Instance/Property	INST01	INST02	INST03
Size	Small	Medium	Large
Number of terminal stations	34	206	88
Number of service trips	424	867	1296
LB (Number of vehicle rotations)	29	67	51

timetable and a lower bound for the number of bus rotations obtained by VSP solution without range limitations.

4.2. Performance and convergence

The experiments are executed on a regular desktop computer (*AMD Ryzen™ 5 3400G @3.7 GHz* with *Radeon™ Vega Graphics*). The solution algorithm is implemented in *C#* and run using mono on a *Ubuntu 20.04*. Analyses are performed with *Python 3.8*, in particular using *pandas* and *numpy* for data management, *statsmodels* for regression analysis, and *matplotlib* for visualizations.

The VNS heuristic exhibits acceptable convergence behaviors for all problem instances and for most parameter configurations. As presented in Figs. 2, convergence is much more stable for the smaller instances than for the largest.

In Fig. B.1 we can see that for all instances and most parameter configurations, the total run-time (15,000 iterations) of the VNS algorithm was well below 10 h, which is acceptable for commercial applications. It is apparent that for the medium-size instance the algorithm exhibits many extreme run-times and an increased average run-time. It stands to reason that this additional complexity arises from the significantly larger number of terminal stops, leading to an increased effort to solve the charging scheduling problem.

For the smaller instance, we can find a strong positive correlation between the total run-time and consumption per trip kilometer (0.44915) and less pronounced negative correlations for the battery capacity and charging power (−0.288 and −0.191). These results are plausible, as the probability of finding energy-infeasible rotations is increased with higher trip consumption and lower battery capacity charging power. The number of charging opportunities to be evaluated after a local search operator is applied grows accordingly. The medium and large instance do not exhibit such effects which fits the observed variance in solution composition, as discussed in the next section.

4.3. Numerical results

The implemented VNS algorithm performs reasonably well for the purpose of this paper. Resulting solutions for the problem instances reach acceptable quality with respect to the known optimal number of vehicles in use (s. Table 3). As can be seen in Fig. 3(a), considering the two characteristics – number of vehicles and charging stations – the algorithm yields similarly distributed solutions for instances INST02 and INST03. Both dot clouds are bi-modal with a vertical split. INST01 requires fewer vehicles in every solution. In addition, fewer charging stations are build than for most solutions for the other problem instances. The individual distributions of both characteristics (see Fig. 3(b)) show that the medium and large instances must have a rather similar solution space. The number of vehicles needed is less dispersed than the number of charging stations, which holds true especially for the larger instances. This fits that degrees of freedom in this optimization problem in large part stem from the location planning, rather than the vehicle scheduling. Considering both figures, the existence of outlying solutions is apparent. There are three solutions without any charging stations installed and a very high number of vehicles in use. In these instances, the solutions could not be improved by adding charging stations. Generally, utilization and incidence exhibit a medium positive correlation (values between 0.37 and 0.5). If a stop is equipped with a charging station, it will be frequently used for recharging. This is consistent with the logic within the algorithm which aims at reducing charging system investments.

Table 4
Correlation matrix for incidence vs centrality and timetable features (INST01).

	Incidence	AvgSquaredDist	Closeness	TripFreq
Incidence	1.000000	−0.113332	−0.067885	0.149901
AvgSquaredDistance	−0.113332	1.000000	−0.877671	0.061452
Closeness	−0.067885	−0.877671	1.000000	0.508906
TripFreq	0.149901	0.061452	0.508906	1.000000

Table 5
Correlation matrix for utilization vs centrality and timetable features (INST01).

	Utilization	AvgSquaredDist	Closeness	TripFreq
Utilization	1.000000	−0.113332	−0.067885	0.149901
AvgSquaredDistance	−0.113332	1.000000	−0.877671	0.061452
Closeness	−0.067885	−0.877671	1.000000	0.508906
TripFreq	0.149901	0.061452	0.508906	1.000000

Table 6
Overview over model and coefficient significance in fitted LR and PR models.

	Sign. Batt.	Sign. Cons.	Sign. Inter.	Sign. Mod.
	Incidence (Logistic Regression Models)			
INST01	11 (73.333%)	10 (66.667%)	11 (73.333%)	15 (44.118%)
INST02	54 (91.525%)	53 (89.831%)	31 (52.542%)	59 (67.045%)
INST03	67 (72.043%)	53 (56.989%)	72 (77.419%)	93 (45.146%)
	Utilization (Poisson Regression Models)			
INST01	15 (88.235%)	15 (88.235%)	16 (94.118%)	17 (50.000%)
INST02	56 (94.915%)	52 (88.136%)	44 (74.576%)	59 (67.045%)
INST03	67 (73.626%)	48 (52.747%)	81 (89.011%)	91 (44.175%)

Legend: Significance level ($p \leq 0.05$); coefficients counted only for sign. models.
Batt. = Battery Capacity; Cons. = Consumption, Inter. = Intercept.

4.4. Stable and persistent structures

While we can draw conclusions about the composition of a resulting charging infrastructure by looking at the incidence, an additional consideration of the actual utilization gives an insight into how integral a charging station is as part of the charging infrastructure in a solution.

4.4.1. Testing Hypothesis 1

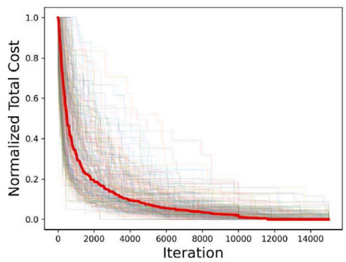
To analyze whether topological or timetable-related feature offered sufficient information to predict charging infrastructure design, three features are introduced in this paper. The average squared distance – such that the overall distance of stop i would be expressed as $D(i) = \frac{\sum_{j \in S} {d_{ij}}^2}{\|S\|}$ where d_{ij} is the kilometer distance between i and j – and closeness centrality – defined as $C_C(i) = \frac{\|S\|}{\sum_{j \in S} d_{ij}}$ as detailed in Freeman (1978) – based on the available deadhead matrix are measured to account for topological properties. The timetable importance is measured by the number of service trips departing from the respective stop (trip frequency).

Correlation analysis yields no discernible pattern of dependence between either of these properties with neither the average utilization, nor the average incidence of charging stations (see Tables 4 and 5). The obtained correlation coefficients indicate a weak linear relationship, at best. There is not enough evidence to support the notion of the ability to identify stable patterns or even persistent structures in the charging infrastructure, just by analyzing the topological or timetable-related properties of stops. This hypothesis is rejected, accordingly.

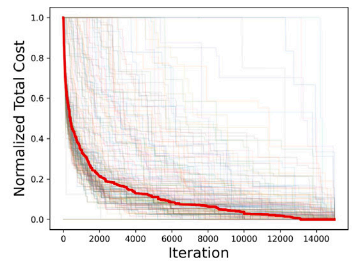
4.4.2. Testing Hypothesis 2

In order to measure the dependence of the features incidence and utilization, we performed correlation analysis against the input parameters for each individual stops. Note that consumption per service trip kilometer was used as a proxy for the overall consumption.

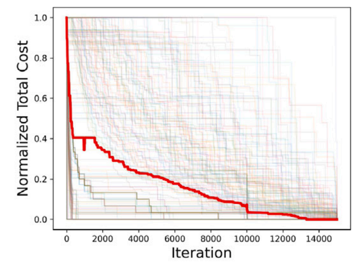
In summary, both features are uncorrelated with the charging power, and the two cost parameters. However, we find medium and strong correlations with the available battery capacity (negative) and the assumed consumption (positive). The correlation can be observed in the data relating to all three problem instances (see Fig. 4) and



(a) Small instance

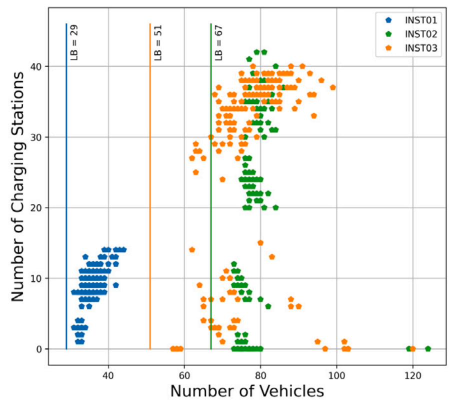


(b) Medium instance

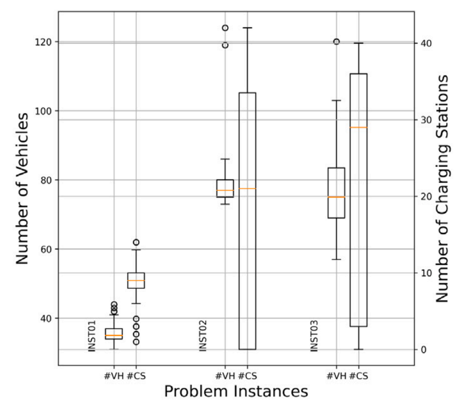


(c) Large instance

Fig. 2. Convergence behavior for three problem instances. Each graph shows the individual convergence for each parameter setting as well as an average convergence graph (red). (To inspect this figure in more detail, we kindly refer the reader to the full-color high-res image included in the web version of this article.)

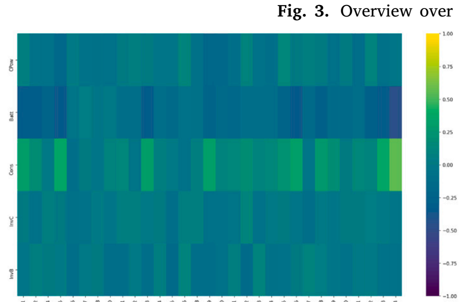


(a) Overview of solutions (number of vehicles and charging stations in use)

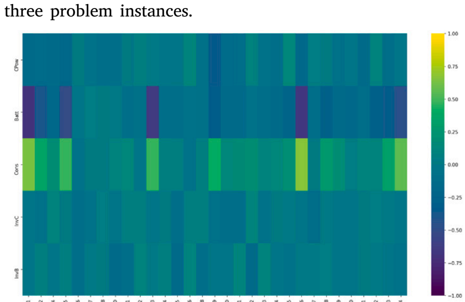


(b) Distribution of number of vehicles and number of charging stations in use

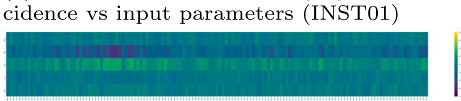
Fig. 3. Overview over solutions for three problem instances.



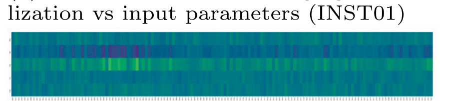
(a) Correlation matrix: charging station incidence vs input parameters (INST01)



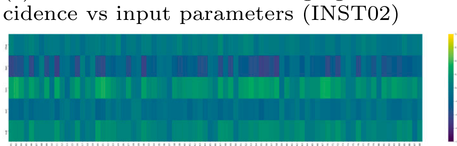
(b) Correlation matrix: charging station utilization vs input parameters (INST01)



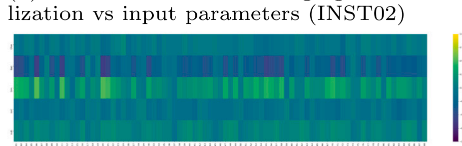
(c) Correlation matrix: charging station incidence vs input parameters (INST02)



(d) Correlation matrix: charging station utilization vs input parameters (INST02)



(e) Correlation matrix: charging station incidence vs input parameters (INST03)



(f) Correlation matrix: charging station utilization vs input parameters (INST03)

Fig. 4. Overview over retrieved solutions for the problem instances. Rows represent parameter charging power, battery capacity, consumption, charging system cost, and bus investment cost (top to bottom). Columns represent terminal stops.

is more pronounced for utilization than for incidence. This means, that, on the one hand, an increased battery capacity is related with both, fewer charging processes at an installed station, and a lower tendency of the algorithm to install a charging system. On the other hand, a greater energy consumption per kilometer is associated with the opposite effect.

Furthermore, several stops are equipped with charging systems in very few solutions. Neither their incidence, nor utilization, correlate with the input parameters. It stands to reason that the instances in which these are used as charging stations would be a random occurrence, and had the stop been blacklisted for example, the algorithm

Table 7
Descriptive analytic measures for the distribution of coefficients in significant LR and PR models.

Instance	Coef.	25%	50%	75%	max	mean	min	std
		Incidence (Logistic Regression Models)						
INST01	Batt	−4.079	−2.598	−1.331	−0.787	−7.425	−37.825	12.406
	Cons	1.342	2.175	4.385	41.241	7.498	0.155	12.812
	intercept	−2.865	−1.286	1.730	37.751	4.042	−4.730	13.712
INST02	Batt	−3.270	−2.832	−2.078	−0.765	−2.739	−5.014	0.918
	Cons	1.420	1.782	2.334	3.888	1.933	−0.529	0.806
	intercept	−1.444	−0.676	−0.146	1.076	−0.821	−3.693	1.047
INST03	Batt	−4.504	−3.472	−2.817	−0.240	−4.417	−65.362	6.527
	Cons	1.362	1.864	2.659	53.583	3.078	−0.000	6.121
	intercept	−2.826	−2.191	−0.877	1.306	−3.082	−55.662	6.601
		Utilization (Poisson Regression Models)						
INST01	Batt	−1.691	−1.208	−0.941	−0.603	−1.555	−3.643	0.938
	Cons	0.996	1.121	1.752	3.219	1.386	0.277	0.831
	intercept	−2.377	−1.042	1.303	3.479	−0.541	−3.635	2.288
INST02	Batt	−2.426	−2.117	−1.762	−0.448	−2.070	−3.438	0.542
	Cons	1.023	1.280	1.628	2.307	1.288	−0.432	0.456
	intercept	−1.330	−0.650	0.113	2.873	−0.645	−3.869	1.251
INST03	Batt	−3.625	−2.705	−2.361	−0.218	−3.625	−53.081	5.382
	Cons	0.993	1.280	1.752	63.293	3.257	−0.000	10.146
	intercept	−2.870	−2.233	−0.999	1.828	−3.854	−65.490	10.485

would have compensated by moving the few charging processes to another stop.

Since we were able to establish a correlation between utilization and incidence and some input parameters, we want to gain more insights into the dependencies for the location planning problem. To corroborate the findings from the correlation analysis, a *logistic regression (LR)* and *Poisson regression (PR)* model were fitted for each stop, regressing incidence – and utilization, respectively – over the normalized input parameters battery capacity and consumption as predictors.

Charging station incidence is the response variable for a binomial logistic regression model. In logistic regression, the goal is to use an additive model of input features (predictors) to predict the probability of the outcome to be in one class — in our case this is the probability that stop becomes a charging station. The charging station utilization is a count variable. Hence, we assumed Poisson distribution and fitted a PR model to investigate the association between the input parameters as outlined above and the number of charging processes in a solution.

In the following, we analyze the fitted models with respect to two aspects, model significance and coefficient significance. We first check for model significance. If a fitted model shows significance, we continue to check the significance of the estimated parameters, as a means to assess, whether varying parameter inputs are predictors for utilization and incidence. If, for the LR case, a fitted model is not significant, we must assume that the probability for a stop to be equipped with a charging station cannot reliably be described through this model. In conclusion, the incidence for this stop would not be explainable by the variation in the selected input parameters. Similarly, for the PR case, if a model is not significant, the number of charging processes at a stop cannot be adequately predicted, using the selected predictors.

Model significance. As a first step, we checked whether significant models – with respect to the log-likely-hood ratio (LLR) – can be fitted using logistic and Poisson regression.[5] For our instances, this holds true. However, as is evident in column "Sign. Mod". in Table 6, less than half of all estimated models in INST01 is significant at the 5% level. The portion of significant models is highest for the medium-sized instance INST02, indicating greater fluctuation in the charging infrastructure due to parameter variations. For the charging station utilization, the regression results are similar.

In conclusion, significant LR and PR models cannot be fitted for all stops. In INST01 and INST03, for over half of all stops, the probability of becoming a charging station cannot be adequately modeled using LR. In INST02 67.05% of stops allow for a regression model to be fit. Moreover, the utilization cannot be reliably explained for at least half the stops in INST01 and INST03, and for about a third in INST02.

Furthermore, whether an LR or PR model will be significant is only very weakly correlated with the structural properties from the previous section. However, medium positive correlation is present between the number of solutions in which a stop becomes a charging station and the significance of the respective regression model. This can be explained through the increase in variance in the outcome variable leaving more information for the model.

Coefficient significance. If a model is significant, it is informative to look at the estimated coefficients which for both, LR and PR, contain information about the strength and direction of a relationship with the outcome variable. Within the significant LR and PR models, significance of the estimated coefficient for the input parameters on 5% level is high which confirms the results of the correlation analysis (s. Table 6).

As can be observed in Table 7, the coefficients are distributed in an expected manner. Battery capacity exerts a strong negative impact on charging station incidence and utilization, whereas the consumption has a positive effect. Thus, higher battery consumption decreases the probability of becoming a charging station for the respective stop. This effect will barely be compensated for by an increased consumption. A similar behavior is apparent for the utilization model.

The model significance in all problem instances is positively correlated with overall charging station incidence. The more frequent a stop is equipped with a charging station, the more likely will it be possible to fit an LR or PR regression model. This is related to another coefficient which is estimated, the intercept. In LR and PR models the intercept can be interpreted as the baseline condition — if all other parameters are at their smallest possible values. For the incidence this can be translated into the probability that a stop becomes a charging station when the normalized input parameters are 0. Stops with particular relevance for the charging infrastructure – i.e. frequently used charging locations – exhibit relatively large intercepts and in comparison small, yet significant coefficients for other input parameters. For charging locations with little importance for the overall charging infrastructure this relation is inverted.

The presented analysis of correlations and regression models yields an understanding of the impact of the selected parameters on the charging infrastructure. From correlations, conclusion can be drawn about important parameters for the problem instance. Regression analyses helps to gain further insights into the (in-)stability of charging locations and to discern important and unimportant charging locations. Two

[5] For more information on model diagnostics, please refer to Tables B.1, B.2, and B.3 (for LR) and B.4 B.5, and B.6 (for PR) in Appendices B.3 and B.4.

possible explanations may lead to a stop having insignificant LR or PR model: (1) The stop must be of negligible importance, hence instances in which it is equipped with a charging station are 'noise'. (2) The stop is part of the majority of charging infrastructures for the respective problem instance, regardless of the combination of technological and economic factors. Thus, it is a candidate for a persistent charging infrastructure. The underlying interplay of utilization and incidence is illustrated in Figs. B.2, B.3, and B.4 in Appendix B.2.

4.5. Discussion

We have demonstrated how the analysis of a multitude of solutions for the CLEVSP based on realistic assumptions about environmental parameters can support the planning process of a robust charging infrastructure for the electrification of a public transport bus system. The analysis and interpretation of structural information does not suffice to determine persistent structure and stable locations. While the analysis shows, that charging station where installed at stops with higher centrality and timetable importance, these are not the sole factors influencing charging station incidence and utilization. The analysis of relationships between incidence and utilization and the input parameters renders a more reliable approach. This approach allows for the distinction of parameter-dependent parts of the resulting charging infrastructure – i.e. stops which are stable only with respect to non-variance in specific parameters – and parts which will be integral for any or the majority of possible charging infrastructure for the respective problem instance. We have demonstrated how regression analysis can yield further information about how and to what extend the input parameters will effect the location planning aspect of the CLEVSP. This helps in finding locations which are suitable to support an optimal vehicle schedule for BEBs.

Limitations. The presented approach depends on the employed solution algorithm and drawn conclusions are in part subject to the implemented logic. This dependence is not unwanted, since it is expected that the VSP solution will be relatively stable and as such remain similar, as long as no fundamental changes to the underlying timetable occur. In practice, it would be advisable to create the solutions with a VSP algorithm similar to the one used in operation.

With respect to the environmental parameters, this study does not include possible adverse and complementary effects between the selected parameters such as vehicle weight and battery capacity, battery capacity and vehicle cost. Furthermore, charging systems allow infinite parallel charging processes and no distinction is made between individual components — i.e. converter and charging system. This might lead to an underestimation of the overall charging system cost. However, from previous studies we can assume that parallel charging does occur very infrequently.

5. Conclusions

In this paper, we address the issue of finding robust opportunity charging infrastructure for fully electrified urban bus systems under simultaneous optimization of charging infrastructure locations and vehicle schedules. We analyze the existing literature and identify a research gap consisting in CLEVSP-solution sensitivity to technological and economical parameters. To fill this gap, this paper proposes a new mathematical model, which optimizes both the charging infrastructure and vehicle schedules in a joint process. As large-scale problem instances cannot be solved exactly, we implement a VNS-based heuristic in order to be able to calculate solutions for realistic problem sizes to deliver a basis for detailed experimental analysis. We conduct comprehensive computational experiments based on real-world instances corresponding to existing anonymized bus networks and vary several parameter values in order to control for the robustness and sensitivity of results.

The experiments indicate that for each of the three studied bus networks, certain terminal bus stops can be identified by the VNS, which are designated for the installation of charging infrastructure in a majority of the parameter settings and thus resemble persistent structures. Comparing our results with the topological and timetable-related properties of the instances shows that it is not possible to trivially identify persistent structures within the charging infrastructure by an a priori analysis of the problem instances. This supports our assumption that the two combinatorial optimization problems are mutually dependent and thus require an algorithmic approach in determining locations for charging infrastructure.

Furthermore, our results highlight that the configuration of electric bus systems in terms of charging infrastructure, bus fleet, and vehicle schedules reacts to varying degrees sensitively to changes in technological parameters consisting of battery capacity, charging power, and energy consumption, as well as economic parameters in form of investment costs for charging stations and electric buses. The highest sensitivity of the location decisions for the charging infrastructure is revealed to changes in battery capacity as well as energy consumption.

We envision further avenues for research. Our analysis approach can support the derivation of instructions for a gradual expansion of the electric bus fleet and the charging infrastructure. In order to conduct appropriate studies, the approach used in this paper needs to be enhanced to include consideration of mixed fleets and to develop a meta-model for gradually increasing the proportion of electric buses in the fleet. Therefore, to solve more complex problem instances, the solution approach can be enhanced by the incorporation of further neighborhood operators, which tackle the location planning of charging stations more explicitly.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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Appendix A. Notation

See Table A.1.

Table A.1
Notation overview.

Sets	Description	
I	Service trips (ordered by increasing departure time)	
V	Vertices (Service trips and depot)	
A	Arcs (Possible connecting and depot trips)	
A'	Possible connecting trips	
S	Terminal stops	
O_s	Service trips with stop $s \in S$ as departure stop	
D_s	Service trips with stop $s \in S$ as arrival stop	
B	Electric buses	
Parameters	**Description**	**Range/Unit**
α_i	Start time of service trip $i \in I$	[min]
β_i	End time of service trip $i \in I$	[min]
n_i	Energy consumption of service trip $i \in I$	[kWh]
$\gamma_{i,j}$	Duration of deadhead trip $(i,j) \in A$	[min]
$n_{i,j}$	Energy consumption of deadhead trip $(i,j) \in A$	[kWh]
$\delta_{i,j}$	Idle time before/after deadhead trip $(i,j) \in A$	[min]
$c_{i,j}^{fix}$	Investment costs per electric bus executing the depot trip $(i,j) \in A$	[MU][a]
$c_{i,j}^{hour}$	Personnel cost for deadhead trip $(i,j) \in A$ and service trip $i \in I$	[MU]
$c_{i,j}^{km}$	Energy consumption costs for deadhead trip $(i,j) \in A$ and service trip $i \in I$	[MU]
c_s	Investment costs per charging station	[€]
p	Charging power of a charging station	[kW]
d	Lower limit for battery discharge	[kWh]
cap	Battery capacity of an electric bus	[kWh]
M	Big M	
Variables	**Description**	**Range/Unit**
$x_{i,j,b}$	Deadhead trip $(i,j) \in A$ is executed by bus b	$\{0,1\}$
y_i^{arr}	Charging process at the arrival stop of service trip $i \in I$	$\{0,1\}$
y_i^{dep}	Charging process at the departure stop of service trip $i \in I$	$\{0,1\}$
z_s	Charging station at bus stop $s \in S$	$\{0,1\}$
$t_{i,b}^{arr}$	Charging time of bus $b \in B$ at the arrival stop of service trip $i \in I$	$\mathbb{R}^+$/[min]
$t_{i,b}^{dep}$	Charging time of bus $b \in B$ at the departure stop of service trip $i \in I$	$\mathbb{R}^+$/[min]
$l_{i,b}^{arr}$	Energy level of bus $b \in B$ at the arrival stop of service trip $i \in I$	$\mathbb{R}^+$/[min]
$l_{i,b}^{dep}$	Energy level of bus $b \in B$ at the departure stop of service trip $i \in I$	$\mathbb{R}^+$/[min]

[a]MU: monetary units.

Appendix B. Results

B.1. Performance

See Fig. B.1.

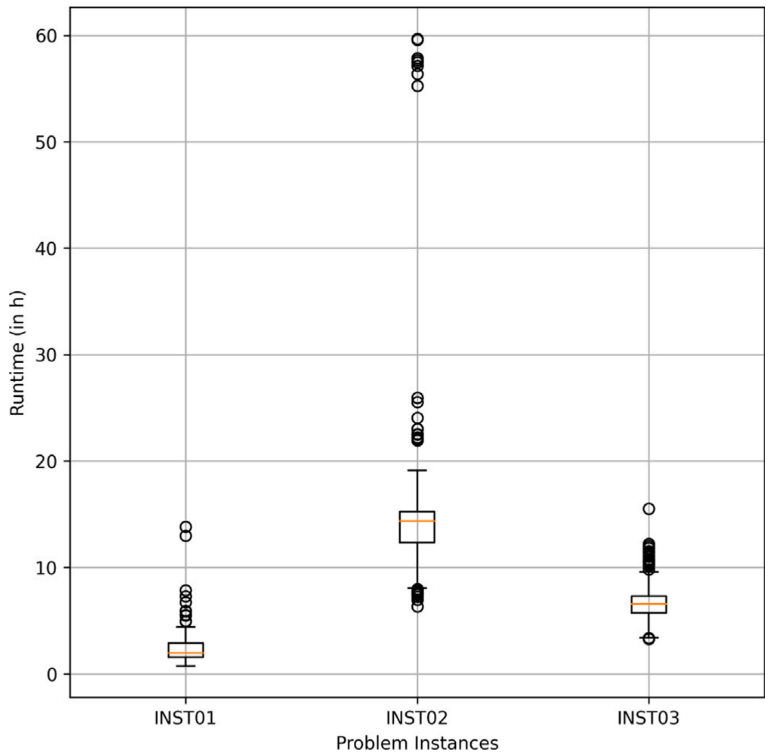

Fig. B.1. Absolute observed run-time per problem instance.

B.2. Composite analysis graphs

See Figs. B.2–B.4.

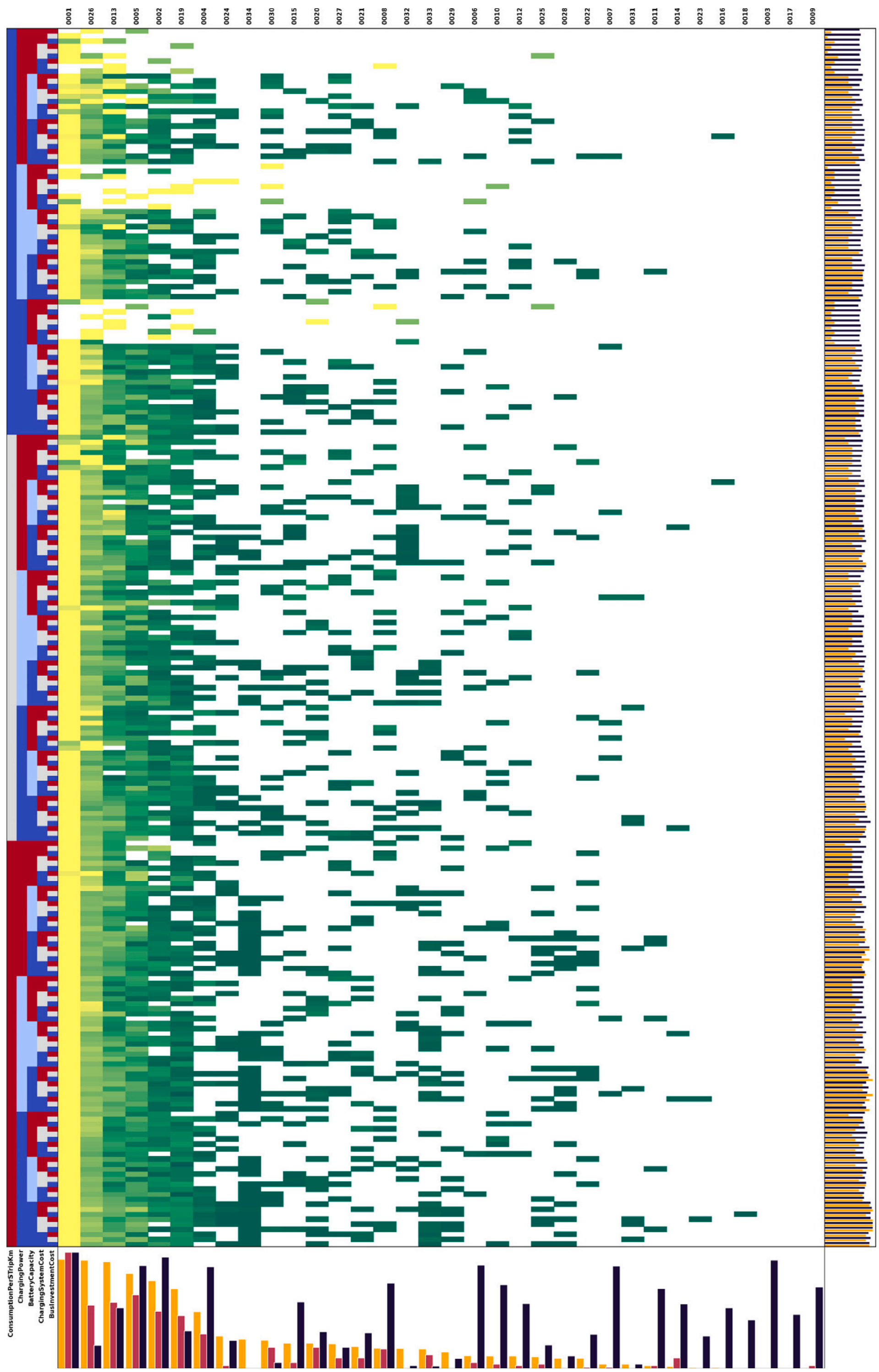

Fig. B.2. Graphical overview of the found solutions for INST01. Rows represent solutions and columns represent stops. The western graph depicts the input parameters (blue: low value; red: high value). The eastern graph compares normalized numbers of vehicle and charging stations in a solution. The southern plot compares the average utilization (yellow), number of departing service trips (orange) and the centrality (purple) of the respective stop. The center plot depicts whether a stop equipped with a charging system and how frequently it is utilized (green: low; yellow: high) relative to other charging stations in the solution. (To inspect this figure in more detail, we kindly refer the reader to the full-color high-res image included in the web version of this article.)

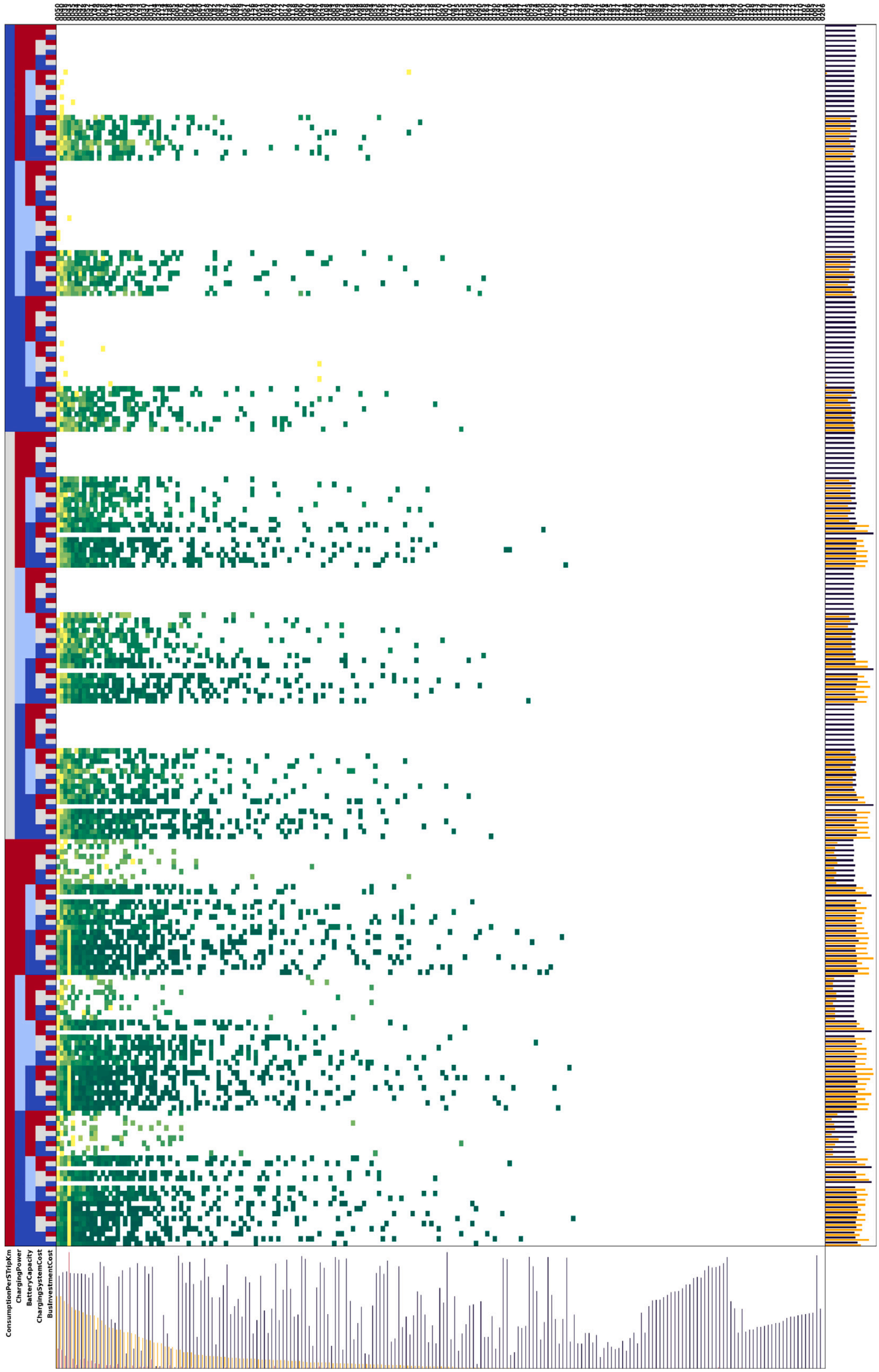

Fig. B.3. Graphical overview of the found solutions for INST02. Rows represent solutions and columns represent stops. The western graph depicts the input parameters (blue: low value; red: high value). The eastern graph compares normalized numbers of vehicle and charging stations in a solution. The southern plot compares the average utilization (yellow), number of departing service trips (orange) and the centrality (purple) of the respective stop. The center plot depicts whether a stop equipped with a charging system and how frequently it is utilized (green: low; yellow: high) relative to other charging stations in the solution.

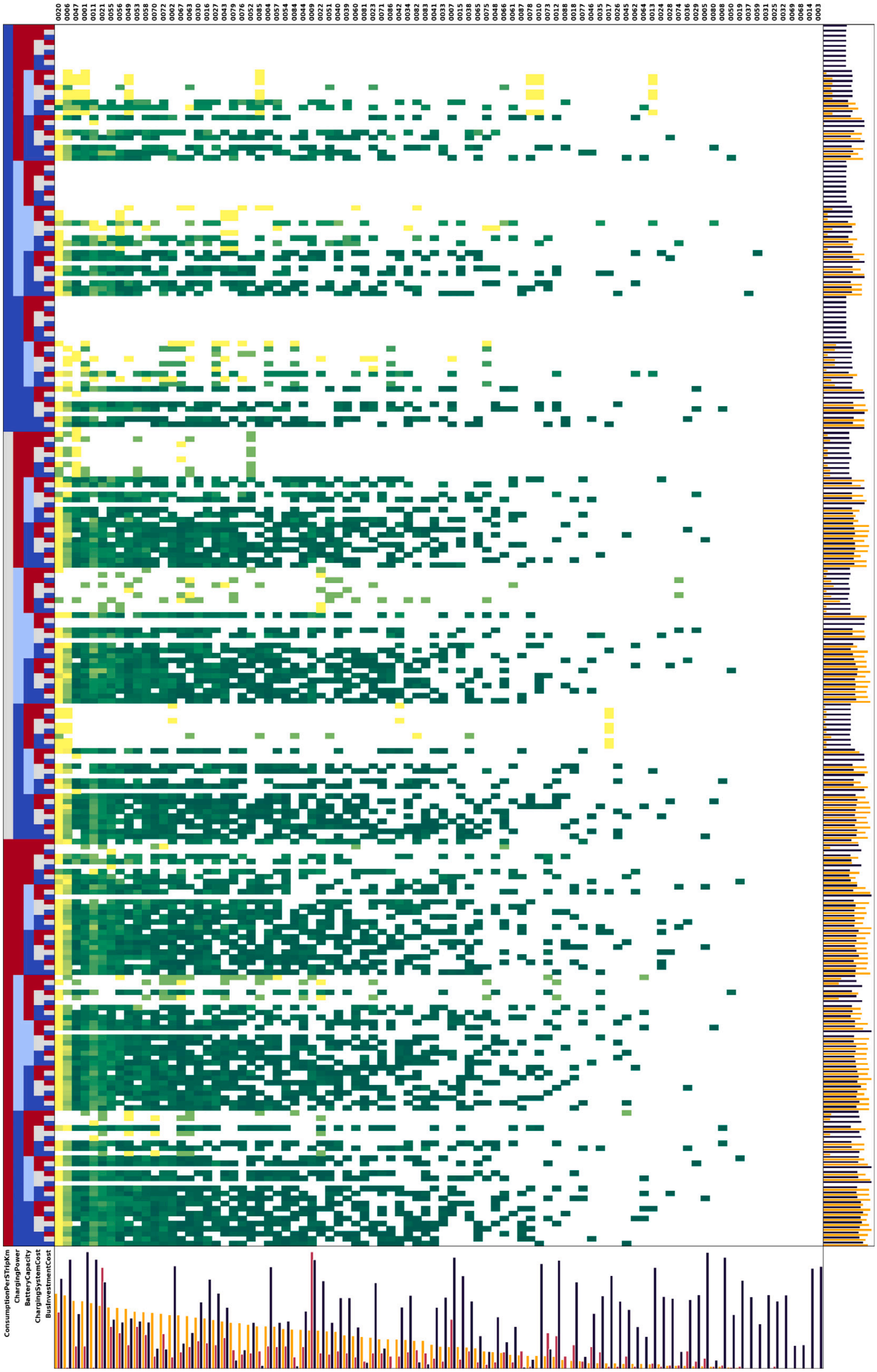

Fig. B.4. Graphical overview of the found solutions for INST03. Rows represent solutions and columns represent stops. The western graph depicts the input parameters (blue: low value; red: high value). The eastern graph compares normalized numbers of vehicle and charging stations in a solution. The southern plot compares the average utilization (yellow), number of departing service trips (orange) and the centrality (purple) of the respective stop. The center plot depicts whether a stop equipped with a charging system and how frequently it is utilized (green: low; yellow: high) relative to other charging stations in the solution.

B.3. Logistic regression results

See Tables B.1–B.3.

Table B.1
Estimated model parameters for INST01 (significance levels: '.' 0.05; '*' 0.01; '**' 0.005; '***' 0.001).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR p-value:	Log-Likelihood:	Pseudo R-squ.:
0001	37.751	−37.8251	41.2408	−53.545	7.338e−16***	−18.696	0.6508
0002	1.5647***	−1.8316***	1.1542*	−134.69	1.259e−07***	−118.80	0.1180
0004	0.35	−1.0658**	0.1555	−168.38	0.002910*	−162.54	0.03468
0005	1.8943***	−2.9327***	3.6724***	−114.94	2.764e−17***	−76.815	0.3317
0006	−1.6827***	−0.2469	−0.634	−84.766	0.4029	−83.857	0.01072
0007	−3.5807***	0.6486	−5.028e−16	−38.494	0.7215	−38.167	0.008478
0008	−1.487***	−0.0182	−0.0848	−113.42	0.9780	−113.40	0.0001958
0010	−2.6865***	0.2757	0.7925	−82.666	0.2648	−81.337	0.01607
0011	−4.8762***	−1.664	2.5586	−28.133	0.03781.	−24.858	0.1164
0012	−1.6917***	−0.772	−0.2613	−82.666	0.2968	−81.451	0.01469
0013	3.9142***	−4.0974***	5.066***	−69.100	7.571e−14***	−38.888	0.4372
0014	−4.2995***	−4.0765	1.7236	−20.394	0.05419	−17.479	0.1429
0015	−1.0386***	−0.768	0.1472	−127.45	0.1304	−125.42	0.01598
0016	−3.5167***	−2.2723	−1.6889	−11.592	0.3911	−10.653	0.08100
0018	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0019	0.5863.	−1.4174***	2.0009***	−150.97	5.836e−10***	−129.71	0.1408
0020	−1.2367***	−0.8823.	0.5967	−127.45	0.02477.	−123.76	0.02902
0021	−1.4411***	−1.2452*	0.8483.	−117.91	0.001898*	−111.64	0.05315
0022	−3.1448***	−0.7874	1.8502*	−73.817	0.003300*	−68.103	0.07740
0023	−34.8813	−64.8608	32.3555	−11.592	0.01154.	−7.1294	0.3849
0024	−1.0546***	−0.693	0.7569.	−144.05	0.01628.	−139.93	0.02859
0025	−2.8074***	−2.598*	2.1749**	−78.334	1.172e−06**	−64.677	0.1743
0026	36.8646	−37.2393	35.7029	−58.989	2.028e−18***	−18.249	0.6906
0027	−0.8776*	−0.8702.	−0.1498	−126.17	0.07999	−123.64	0.02002
0028	−3.6949***	−4.0612**	3.4577***	−73.817	2.136e−10***	−51.550	0.3017
0029	−2.2669***	−1.0791.	1.5298*	−100.17	0.0004956**	−92.559	0.07597
0030	−0.7733*	−0.9008.	−1.509e−16	−134.69	0.05601	−131.81	0.02140
0031	−3.9982***	−1.6838	2.0062	−38.494	0.02144.	−34.651	0.09982
0032	−1.2862***	−2.0168***	0.7513	−111.87	3.597e−05**	−101.63	0.09147
0033	−2.9234***	−3.8758***	3.7034***	−110.29	1.556e−17***	−71.586	0.3509
0034	−4.7303***	−9.303***	9.1626***	−138.00	8.958e−43***	−41.185	0.7016

Table B.2
Estimated model parameters for INST02. (significance levels: '.' 0.05; '*' 0.01; '**' 0.005; '***' 0.001).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR p-value:	Log-Likelihood:	Pseudo R-squ.:
0001	−4.2995***	−4.0765	1.7236	−20.394	0.05419	−17.479	0.1429
0003	−3.6846***	−2.4168.	2.2024.	−47.797	0.0009893**	−40.878	0.1447
0004	−1.2193***	−3.1632***	0.9329.	−108.68	2.346e−08***	−91.110	0.1617
0005	−4.382*	−83.3303	−1.283e−16	−6.4910	0.3320	−5.3883	0.1699
0006	−2.4724***	−3.3495*	1.2656	−61.608	0.0001165**	−52.550	0.1470
0007	−2.9857***	−1.7196.	1.3927	−56.302	0.01013.	−51.710	0.08157
0008	−4.382*	−83.3303	−1.916e−15	−6.4910	0.3320	−5.3883	0.1699
0009	−4.1194***	−2.0575.	2.6611*	−47.797	0.0006193**	−40.410	0.1545
0010	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0011	−1.872***	−4.3942***	1.5617*	−88.843	2.176e−09***	−68.898	0.2245
0012	−34.8813	−64.8608	32.3555	−11.592	0.01154.	−7.1294	0.3849
0014	−4.7517*	−59.9943	1.7105	−11.592	0.07290	−8.9730	0.2259
0015	−2.1187***	−7.3443.	0.3087	−44.794	0.0001010**	−35.593	0.2054
0016	−2.17***	−1.4983*	1.8372***	−108.68	3.317e−06**	−96.062	0.1161
0017	−2.6482***	−3.5635*	1.6663.	−64.165	1.296e−05**	−52.911	0.1754
0018	−2.4401***	−2.7423*	1.1826	−64.165	0.0004296**	−56.412	0.1208
0019	0.0047	−4.1225***	2.6525***	−166.70	9.191e−27***	−106.75	0.3596
0020	−1.4408***	−4.7671***	1.3623*	−100.17	3.029e−11***	−75.949	0.2418
0021	−1.9808***	−2.188.	−0.5045	−50.711	0.02930.	−47.181	0.06961
0022	−2.8174***	−6.2506.	0.8332	−35.176	0.001739*	−28.821	0.1807
0023	−0.9145*	−3.5315***	2.2029***	−147.67	1.969e−18***	−106.90	0.2761
0026	−3.8289***	−2.6577	2.0276.	−38.494	0.005175*	−33.230	0.1367

(continued on next page)

Table B.2 (*continued*).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR *p*-value:	Log-Likelihood:	Pseudo R-squ.:
0027	−3.2351***	−4.1505.	1.2721	−35.176	0.005560*	−29.984	0.1476
0028	0.0316	−4.5551***	2.501***	−164.96	8.165e−28***	−102.59	0.3781
0029	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0030	−0.9809*	−3.2375***	1.8073***	−140.10	9.547e−15***	−107.82	0.2304
0031	−0.8774*	−3.8042***	1.5805***	−134.69	3.708e−15***	−101.46	0.2467
0033	−0.3298	−3.9713***	1.5287***	−150.97	8.331e−19***	−109.34	0.2757
0035	−2.1444***	−3.8223***	1.5729*	−80.522	1.474e−07***	−64.792	0.1954
0036	−0.7111.	−2.7051***	1.9166***	−155.36	3.895e−15***	−122.18	0.2136
0038	1.1266***	−6.4637***	4.9924***	−164.96	6.296e−40***	−74.696	0.5472
0039	−2.4577***	−5.7639*	1.0897	−50.711	3.806e−05**	−40.535	0.2007
0040	1.3059***	−5.7594***	4.6158***	−161.20	1.528e−36***	−78.731	0.5116
0041	−0.1496	−3.9449***	3.1448***	−167.69	1.527e−27***	−105.94	0.3682
0042	0.641.	−5.9822***	3.6481***	−168.43	5.926e−38***	−82.714	0.5089
0043	1.3033***	−7.1942***	4.6209***	−166.93	3.203e−43***	−69.085	0.5862
0044	0.7326.	−6.2442***	3.836***	−168.42	2.782e−39***	−79.639	0.5271
0045	0.5819.	−5.5728***	4.1416***	−167.97	1.055e−36***	−85.132	0.4932
0046	−2.4007***	−6.6371.	0.3679	−38.494	0.0008472**	−31.420	0.1838
0047	−1.0092**	−2.7589***	1.5211***	−136.92	1.249e−11***	−111.82	0.1834
0048	0.3757	−4.9501***	3.1877***	−168.33	1.248e−32***	−94.872	0.4364
0050	1.2622***	−6.0237***	5.0407***	−161.20	8.735e−38***	−75.869	0.5293
0051	−2.6862***	−3.957**	1.9709*	−69.100	5.065e−07***	−54.604	0.2098
0052	0.1654	−4.4155***	2.8948***	−167.84	3.239e−29***	−102.24	0.3908
0053	−3.9982***	−1.6838	2.0062	−38.494	0.02144.	−34.651	0.09982
0054	−0.5924	−4.712***	2.6587***	−155.36	6.807e−26***	−97.408	0.3730
0057	−2.2249***	−4.8446**	1.6115.	−73.817	5.739e−08***	−57.144	0.2259
0058	−1.5736***	−4.0127***	0.8532	−84.766	2.799e−07***	−69.677	0.1780
0060	−1.809***	−3.98***	1.3856.	−88.843	1.831e−08***	−71.027	0.2005
0061	−2.6007***	−3.8309**	1.9994*	−73.817	1.666e−07***	−58.209	0.2114
0062	−2.4776***	−3.3236***	2.6138***	−100.17	1.235e−11***	−75.052	0.2507
0064	−1.7144***	−2.8174***	1.2892.	−98.370	3.756e−07***	−83.575	0.1504
0066	−0.7733*	−2.9743***	2.6362***	−161.20	4.147e−20***	−116.57	0.2769
0067	−2.181***	−3.4668***	1.5571*	−80.522	4.959e−07***	−66.005	0.1803
0068	−3.7072***	−2.6446.	2.3981*	−50.711	0.0002163**	−42.273	0.1664
0069	−2.8566***	−2.9668*	1.7491.	−61.608	7.411e−05**	−52.098	0.1544
0070	−5.555*	−4.8289	3.601	−24.366	0.002629*	−18.425	0.2438
0072	−2.4367***	−4.0777*	1.4425.	−64.165	7.909e−06**	−52.417	0.1831
0074	−76.6138	−0.7013	72.5039	−6.4910	0.3196	−5.3504	0.1757
0075	−2.7096***	−5.2785	−3.976e−16	−28.133	0.01933.	−24.187	0.1403
0078	−3.1573***	−3.3062	0.5282	−28.133	0.06763	−25.439	0.09575
0080	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0081	−5.4345*	−4.1161	3.126	−20.394	0.01669.	−16.301	0.2007
0082	−2.5822***	−2.7428**	2.1109**	−84.766	2.041e−07***	−69.362	0.1817
0083	−2.6199***	−3.3864***	2.2447**	−82.666	1.750e−08***	−64.805	0.2161
0086	−2.5818***	−4.5215***	2.1657*	−76.100	7.058e−09***	−57.330	0.2466
0089	−3.5951***	−2.6311.	2.0058.	−44.794	0.001854*	−38.503	0.1404
0090	−3.2581***	−47.2474	−9.509e−16	−16.165	0.03567.	−12.831	0.2062
0092	−3.737***	−4.7348	1.3381	−24.366	0.02609.	−20.720	0.1496
0093	−23.3344	−3.343	20.895	−16.165	0.009759*	−11.535	0.2864
0094	−6.8163***	−0.2398	4.719.	−38.494	0.0009695**	−31.555	0.1803
0095	−2.8045***	−58.7986	−1.0851	−16.165	0.02736.	−12.566	0.2226
0096	−2.5046***	−3.571**	1.8962*	−76.100	2.825e−07***	−61.020	0.1982
0098	−2.0771***	−7.0002.	−2.286e−16	−41.696	0.0003214**	−33.653	0.1929
0102	−3.0169***	−2.3758*	2.0124*	−66.661	5.515e−05**	−56.855	0.1471
0103	−2.7079***	−6.0886**	2.1715*	−66.661	8.451e−09***	−48.072	0.2789
0108	−2.5748***	−2.5696.	0.7701	−50.711	0.009667*	−46.072	0.09148
0109	−2.0796***	−4.5041*	0.8376	−61.608	2.509e−05**	−51.015	0.1719
0111	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0112	−2.0089***	−3.4837**	1.1328	−76.100	5.700e−06**	−64.025	0.1587
0113	−5.719*	−2.8909	3.5658	−24.366	0.009082*	−19.665	0.1929
0114	−1.2559***	−2.8086***	1.5742***	−127.45	7.705e−11***	−104.17	0.1827
0116	−3.9613***	−3.3349	1.7442	−28.133	0.02236.	−24.333	0.1351

(*continued on next page*)

Table B.2 (*continued*).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR *p*-value:	Log-Likelihood:	Pseudo R-squ.:
0117	−5.2056*	−2.2723	1.6889	−11.592	0.3911	−10.653	0.08100
0118	−3.5456***	−3.0442*	2.677*	−61.608	2.785e−06**	−48.817	0.2076
0119	−3.5051***	−2.9103*	3.0079***	−73.817	3.321e−08***	−56.597	0.2333
0120	−2.6651***	−3.7289	2.442e−16	−31.728	0.03366.	−28.337	0.1069
0124	−0.4539	−3.2557***	1.9245***	−157.91	3.329e−18***	−117.67	0.2549
0125	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0126	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0127	−3.5715***	−3.2423*	2.8362**	−64.165	4.816e−07***	−49.619	0.2267
0128	−2.8261***	−2.9542*	2.0577*	−71.485	2.966e−06**	−58.756	0.1781
0130	−4.382*	−83.3303	−2.003e−15	−6.4910	0.3320	−5.3883	0.1699
0131	−0.0454	−3.8384***	1.3893**	−157.30	2.097e−19***	−114.29	0.2734
0134	−3.0198***	−4.8726.	1.4017	−41.696	0.0005674**	−34.222	0.1793
0135	−23.329	−3.343	20.8896	−16.165	0.009759*	−11.535	0.2864
0138	−4.3869***	−4.7706	2.2155	−24.366	0.01085.	−19.843	0.1856
0140	−2.3692***	−3.2412.	0.7258	−53.545	0.001764*	−47.204	0.1184
0141	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0144	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0145	−12.1279	−2.4694	10.652	−35.176	1.151e−05**	−23.803	0.3233
0146	−34.8811	−64.8608	32.3553	−11.592	0.01154.	−7.1294	0.3849
0147	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0149	−0.0776	−3.4519***	2.5734***	−167.53	2.315e−23***	−115.41	0.3111
0154	−1.2998***	−2.6529***	1.2895*	−119.35	1.007e−08***	−100.93	0.1543
0155	−4.728***	−0.7027	1.0589	−16.165	0.6891	−15.792	0.02304
0156	−2.228***	−2.4864*	1.1487	−73.817	0.0002274**	−65.428	0.1136
0160	−2.4508***	−2.9077*	1.3352.	−66.661	0.0001159**	−57.598	0.1360
0162	−3.65***	−1.0736	0.9151	−31.728	0.3623	−30.713	0.03200
0163	−34.8813	−64.8608	32.3555	−11.592	0.01154.	−7.1294	0.3849
0164	−2.3565***	−2.3177**	1.8641**	−90.823	1.140e−06**	−77.138	0.1507
0165	−3.5167***	−2.2723	−1.6889	−11.592	0.3911	−10.653	0.08100
0167	−4.7547***	−4.264.	3.2361.	−35.176	0.0002271**	−26.786	0.2385
0168	−5.4201***	−1.2595	3.8289*	−44.794	0.0003416**	−36.812	0.1782
0169	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0172	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0173	−3.8023***	−2.346	1.7546	−35.176	0.02091.	−31.308	0.1100
0175	−4.3869***	−4.7706	2.2155	−24.366	0.01085.	−19.843	0.1856
0177	−40.4982	−63.5719	37.2401	−6.4910	0.1093	−4.2771	0.3411
0178	−4.0707***	−1.8781	1.3174	−24.366	0.1910	−22.711	0.06794
0182	−1.4825***	−2.7016**	0.2766	−82.666	0.0001636**	−73.948	0.1055
0183	−2.2792***	−1.8678.	7.849e−17	−50.711	0.07390	−48.106	0.05137
0184	−2.803***	−3.6665.	1.3568	−50.711	0.0004350**	−42.971	0.1526
0188	−1.5592***	−2.508***	1.608**	−117.91	5.679e−09***	−98.919	0.1610
0189	−0.5258	−3.4718***	1.631***	−150.18	7.720e−17***	−113.08	0.2470
0190	−34.8811	−64.8608	32.3554	−11.592	0.01154.	−7.1294	0.3849
0192	−3.0684***	−2.8412.	1.4582	−47.797	0.002537*	−41.820	0.1250
0193	−0.7636.	−3.2972***	1.5979***	−143.09	8.300e−15***	−110.67	0.2266
0195	−5.0039*	−50.6181	2.5716	−16.165	0.01133.	−11.684	0.2772
0196	−34.8813	−64.8608	32.3555	−11.592	0.01154.	−7.1294	0.3849
0197	−0.5462.	−2.3228***	1.158*	−150.97	2.772e−10***	−128.97	0.1458
0198	−2.1908***	−4.8147.	2.033e−17	−41.696	0.002201*	−35.577	0.1467
0199	−3.4096***	−3.705.	1.8052	−41.696	0.001048*	−34.835	0.1645
0200	−5.2056*	−2.2723	1.6889	−11.592	0.3911	−10.653	0.08100
0202	−55.6619	−65.3615	53.5825	−16.165	0.001175*	−9.4185	0.4173
0203	−0.8388*	−3.1473***	1.0321.	−128.72	8.151e−11***	−105.49	0.1805
0204	−1.5221***	−3.5309***	2.3542***	−129.96	6.642e−16***	−95.012	0.2689
0205	−1.6888***	−2.4504***	1.7405***	−116.44	4.862e−09***	−97.295	0.1644

Table B.3
Estimated model parameters for INST03. (significance levels: '.' 0.05; '*' 0.01; '**' 0.005; '***' 0.001).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR *p*-value:	Log-Likelihood:	Pseudo R-squ.:
0001	0.8162*	−3.6495***	2.5674***	−165.29	1.056e−24***	−110.08	0.3340
0002	−0.4509	−3.3896***	3.3293***	−167.69	9.313e−26***	−110.06	0.3437
0004	−0.5559.	−2.9139***	2.0648***	−159.63	2.501e−17***	−121.41	0.2395
0005	−4.5595***	−2.8606	2.1938	−24.366	0.03697.	−21.069	0.1353
0006	1.0763***	−3.4312***	2.4956***	−160.17	1.049e−22***	−109.57	0.3160
0007	−1.6132***	−1.5672**	1.2524*	−116.44	3.619e−05**	−106.21	0.08783
0008	−4.9366***	0.7933	0.7827	−20.394	0.6607	−19.980	0.02032
0009	−0.6615.	−3.7477***	2.251***	−153.97	1.128e−20***	−108.04	0.2983
0010	−1.1668**	−2.0783*	−0.5288	−84.766	0.001263*	−78.092	0.07874
0011	0.7398.	−5.014***	3.8818***	−166.45	7.753e−34***	−90.212	0.4580
0012	−2.2513***	−0.9858	0.8315	−80.522	0.05775	−77.670	0.03541
0013	−2.0505***	−1.021	−2.5849.	−38.494	0.01670.	−34.401	0.1063
0015	−1.514***	−1.991***	1.2818*	−116.44	1.884e−06**	−103.26	0.1132
0016	−0.1319	−3.5749***	2.4486***	−166.19	2.882e−23***	−114.29	0.3123
0017	−3.5447***	0.9517	6.096e−16	−44.794	0.4281	−43.946	0.01894
0018	−3.3259***	−2.6566*	2.3149*	−61.608	2.498e−05**	−51.011	0.1720
0019	−36.6057	1.2927	32.2141	−11.592	0.08215	−9.0923	0.2156
0020	0.7694*	−2.847***	2.7002***	−158.50	5.658e−20***	−114.18	0.2796
0021	0.116	−4.058***	3.8879***	−167.69	3.370e−30***	−99.828	0.4047
0022	−1.3111***	−1.125*	1.8925***	−153.25	1.620e−08***	−135.31	0.1171
0023	−0.9716**	−2.0389***	1.3026**	−141.12	1.583e−08***	−123.16	0.1273
0024	−3.3766***	−3.3824.	1.548	−38.494	0.004642*	−33.121	0.1396
0026	−2.6498***	−2.5817.	0.594	−44.794	0.02293.	−41.019	0.08428
0027	−0.1481	−2.8317***	1.8345***	−165.29	4.571e−17***	−127.67	0.2276
0028	−2.7096***	−5.2785	−4.763e−16	−28.133	0.01933.	−24.187	0.1403
0029	−2.9982***	−1.8715	−0.6269	−24.366	0.3092	−23.193	0.04817
0030	0.026	−4.6316***	2.948***	−166.70	6.713e−30***	−99.527	0.4030
0033	−1.4388***	−1.8724***	1.1558*	−117.91	6.878e−06**	−106.02	0.1008
0034	−1.0912***	−2.2487***	1.3923**	−135.82	3.619e−09***	−116.38	0.1431
0035	−3.5918***	−0.5401	1.4147	−47.797	0.1399	−45.830	0.04115
0036	−3.7708***	−1.6425	1.0796	−28.133	0.2186	−26.613	0.05405
0037	−3.2581**	−63.572	−44.8323	−6.4910	0.1093	−4.2771	0.3411
0038	−1.7359***	−2.4902***	1.7771***	−114.94	4.139e−09***	−95.639	0.1679
0039	−0.5636.	−2.8444***	1.1864*	−145.90	3.305e−12***	−119.46	0.1812
0040	−0.736*	−2.2511***	1.5019***	−151.75	4.406e−11***	−127.91	0.1571
0041	−1.701***	−1.8012***	1.7331***	−123.51	1.007e−07***	−107.40	0.1304
0042	−1.3478***	−2.0772***	1.7819***	−136.92	6.208e−10***	−115.72	0.1548
0043	−0.1435	−2.8475***	1.7004***	−164.24	1.583e−16***	−127.86	0.2215
0044	−0.5021	−2.8321***	1.562***	−154.67	1.938e−14***	−123.10	0.2041
0045	−4.3167***	−0.7386	2.218.	−41.696	0.03200.	−38.254	0.08255
0046	−2.6322***	−1.99.	0.5424	−47.797	0.05440	−44.885	0.06091
0047	0.6194.	−2.9735***	2.3537***	−164.96	3.337e−20***	−120.11	0.2719
0048	−1.9195***	−1.2264.	1.0618.	−100.17	0.003047*	−94.375	0.05784
0049	0.3202	−2.9972***	2.117***	−168.33	8.455e−20***	−124.42	0.2609
0050	−4.11***	−0.7013	−3.628e−16	−16.165	0.8927	−16.051	0.007024
0051	−0.8652*	−2.3086***	1.8021***	−152.51	1.584e−12***	−125.34	0.1782
0052	−0.6765.	−2.1197***	1.9281***	−161.20	3.742e−13***	−132.59	0.1775
0053	−0.2194	−2.8978***	2.8412***	−168.38	7.892e−22***	−119.79	0.2886
0054	−0.6035.	−2.8931***	1.8683***	−156.02	5.980e−16***	−120.97	0.2247
0055	0.4785	−4.6745***	3.457***	−168.09	6.193e−32***	−96.228	0.4275
0056	0.5166	−3.6476***	2.38***	−168.19	2.005e−24***	−113.62	0.3244
0057	−0.355	−3.0196***	1.7059***	−159.08	1.517e−16***	−122.65	0.2290
0058	0.2585	−4.7619***	3.2998***	−168.33	6.245e−32***	−96.483	0.4268
0059	−3.2581**	−63.572	−44.8323	−6.4910	0.1093	−4.2771	0.3411
0060	−0.9264**	−2.0237***	1.3421**	−144.05	7.896e−09***	−125.39	0.1295
0061	−2.0345***	−0.5266	0.4755	−88.843	0.3507	−87.796	0.01179
0062	−2.5516***	−1.9051	−1.145e−15	−41.696	0.1254	−39.620	0.04980
0063	−0.2378	−2.0028***	1.7507***	−167.34	1.658e−12***	−140.22	0.1621
0064	−3.9567***	−0.7329	1.7456	−41.696	0.08591	−39.242	0.05887
0065	−1.4482***	−2.8586***	1.3933*	−113.42	5.802e−09***	−94.454	0.1672
0066	−1.923***	−2.4139***	1.4315*	−96.537	2.175e−06**	−83.498	0.1351

(*continued on next page*)

Table B.3 (*continued*).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR *p*-value:	Log-Likelihood:	Pseudo R-squ.:
0067	−0.7084*	−1.9314***	2.6407***	−167.53	9.499e−17***	−130.63	0.2202
0070	−0.2114	−4.0206***	3.5774***	−168.19	3.043e−29***	−102.52	0.3904
0071	−1.1865***	−2.4327***	1.7246***	−138.00	3.709e−11***	−113.99	0.1740
0072	0.2027	−3.3548***	2.1393***	−168.09	9.936e−22***	−119.73	0.2877
0073	−2.6347***	−1.113	1.5565*	−82.666	0.002187*	−76.540	0.07410
0074	−4.2762***	0.6407	0.519	−28.133	0.7091	−27.789	0.01222
0075	−1.5324***	−0.958.	0.2994	−101.93	0.09236	−99.552	0.02337
0076	−0.1377	−3.1856***	1.7133***	−162.61	3.939e−18***	−122.53	0.2465
0077	−3.6933***	−0.765	2.0899*	−58.989	0.006684*	−53.981	0.08490
0078	−1.8036***	−1.9313*	0.661	−84.766	0.001830*	−78.463	0.07437
0079	−0.2617	−2.3365***	1.4648***	−163.04	1.100e−12***	−135.51	0.1689
0080	−3.0882***	−2.2859	−0.7876	−20.394	0.2777	−19.113	0.06282
0081	−0.975*	−4.0192***	2.1886***	−142.12	5.045e−19***	−99.988	0.2964
0082	−0.9869*	−2.9258***	1.4076**	−133.54	1.620e−11***	−108.70	0.1861
0083	−1.5166***	−2.9091***	2.2731***	−133.54	3.028e−14***	−102.41	0.2331
0084	−0.6081.	−2.5739***	1.6602***	−155.36	1.369e−13***	−125.74	0.1907
0085	−0.4721	−1.7767***	1.2138**	−159.63	1.563e−08***	−141.66	0.1126
0086	−0.747.	−2.4766***	0.9856.	−138.00	3.122e−09***	−118.42	0.1419
0087	−2.4915***	−2.6449**	2.0244**	−86.825	2.872e−07***	−71.762	0.1735
0088	−2.2795***	−2.1635.	0.7591	−64.165	0.005743*	−59.005	0.08041

B.4. Poisson regression results

See Tables B.4–B.6.

Table B.4
Estimated model parameters for INST01. (significance levels: '.' 0.05; '*' 0.01; '**' 0.005; '***' 0.001).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR *p*-value:	Log-Likelihood:	Pseudo R-squ.:
0001	3.4787***	−1.2505***	1.0494***	−2930.5	0.000***	−1101.8	0.6240
0002	1.3034***	−1.2076***	0.9961***	−905.87	2.614e−82***	−718.02	0.2074
0004	0.0512	−0.6285***	0.6182***	−406.23	2.545e−08***	−388.75	0.04305
0005	1.908***	−1.4863***	1.2756***	−1508.2	3.829e−251***	−931.62	0.3823
0006	−1.8756***	−0.0646	−0.4027	−94.835	0.6623	−94.423	0.004345
0007	−3.6074***	0.6235	−1.647e−16	−38.663	0.7306	−38.349	0.008119
0008	−1.3757***	0.0582	0.0909	−171.20	0.9372	−171.13	0.0003790
0010	−2.5776***	0.2849	0.6908	−98.703	0.2417	−97.283	0.01439
0011	−4.8796***	−1.6	2.4765	−28.208	0.04162.	−25.029	0.1127
0012	−1.7609***	−0.553	−0.0938	−101.44	0.4470	−100.63	0.007937
0013	2.4672***	−1.6912***	1.0632***	−1668.9	0.000***	−843.15	0.4948
0014	−4.3117***	−3.9835	1.6682	−20.427	0.05743	−17.570	0.1399
0015	−1.3324***	−0.5106	0.2962	−150.86	0.1785	−149.14	0.01142
0016	−3.543***	−2.2491	−1.6682	−11.600	0.3946	−10.670	0.08017
0018	−34.7257	−49.5184	31.4298	−6.4931	0.1111	−4.2958	0.3384
0019	0.7138***	−1.0018***	1.2939***	−766.40	5.519e−66***	−616.13	0.1961
0020	−1.0418***	−0.8178*	0.7171*	−216.14	0.0001706**	−207.47	0.04014
0021	−1.4472***	−1.0465**	1.1207***	−192.98	1.528e−06**	−179.59	0.06939
0022	−3.1538***	−0.6027	1.7524*	−83.934	0.002286*	−77.853	0.07245
0023	−53.796	−66.3303	51.1933	−11.600	0.01235.	−7.2054	0.3788
0024	−1.2323***	−0.5477	0.5524	−171.73	0.02311.	−167.96	0.02194
0025	−2.7644***	−2.159*	1.7524*	−82.548	8.421e−06**	−70.863	0.1416
0026	2.8703***	−1.0725***	1.0147***	−1684.6	0.000***	−824.10	0.5108
0027	−0.9446***	−0.789.	0.0822	−181.29	0.02984.	−177.77	0.01937
0028	−3.6355***	−3.3448**	2.8613***	−74.844	3.667e−09***	−55.420	0.2595
0029	−2.3767***	−0.8968	1.2803*	−102.82	0.001600*	−96.382	0.06261
0030	−0.8252***	−0.9409**	0.2767	−200.51	0.001927*	−194.25	0.03118
0031	−3.6775***	−1.8351	1.6682	−42.598	0.01884.	−38.626	0.09323
0032	−1.538***	−1.6809**	0.5794	−115.73	0.0002061**	−107.24	0.07334
0033	−2.2514***	−3.6427***	2.6966***	−189.19	2.729e−29***	−123.42	0.3476
0034	−2.9567***	−2.959***	3.2189***	−146.69	6.308e−25***	−90.965	0.3799

Table B.5
Estimated model parameters for INST02. (significance levels: ‘.’ 0.05; ‘*’ 0.01; ‘**’ 0.005; ‘***’ 0.001).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR *p*-value:	Log-Likelihood:	Pseudo R-squ.:
0001	−4.3117***	−3.9835	1.6682	−20.427	0.05743	−17.570	0.1399
0003	−3.7052***	−2.2491.	2.0386.	−48.098	0.001497*	−41.594	0.1352
0004	−1.4662***	−2.6097***	0.73	−117.11	1.915e−07***	−101.64	0.1321
0005	−4.3944*	−58.791	−2.511e−16	−6.4931	0.3333	−5.3944	0.1692
0006	−2.2173***	−3.3641*	0.8109	−68.810	9.167e−05**	−59.513	0.1351
0007	−3.0402***	−1.6.	1.2803	−56.775	0.01380.	−52.492	0.07544
0008	−4.3944*	−58.791	−8.860e−16	−6.4931	0.3333	−5.3944	0.1692
0009	−4.1244***	−1.8984	2.4765.	−48.098	0.0009683**	−41.158	0.1443
0010	−34.7268	−49.5517	31.431	−6.4931	0.1111	−4.2958	0.3384
0011	−1.8506***	−4.3099***	1.3417*	−111.10	1.625e−11***	−86.257	0.2236
0012	−53.796	−66.3303	51.1933	−11.600	0.01235.	−7.2054	0.3788
0014	−4.7551*	−52.6697	1.6682	−11.600	0.07487	−9.0078	0.2234
0015	−2.233***	−6.9969.	0.2736	−45.047	0.0001519**	−36.254	0.1952
0016	−1.9869***	−1.1953*	1.3541***	−136.39	7.192e−06**	−124.55	0.08683
0017	−2.3694***	−3.7483**	1.3137.	−77.617	1.261e−06**	−64.034	0.1750
0018	−2.5285***	−2.5236*	1.0449	−64.848	0.0007896**	−57.704	0.1102
0019	−0.1246	−2.3486***	0.9322***	−309.77	8.318e−30***	−242.81	0.2162
0020	−1.7357***	−3.5904***	1.1669*	−110.59	3.669e−10***	−88.862	0.1965
0021	−1.8941***	−2.1012.	−0.6092	−58.161	0.01649.	−54.056	0.07058
0022	−2.8764***	−6.0117.	0.7683	−35.309	0.002165*	−29.173	0.1738
0023	−1.0907***	−2.4914***	1.3045***	−194.36	6.575e−18***	−154.80	0.2036
0026	−3.9521***	−2.2491	2.1197.	−42.598	0.003722*	−37.004	0.1313
0027	−3.2746***	−3.9835.	1.1903	−35.309	0.006719*	−30.306	0.1417
0028	−0.0881	−2.5853***	0.9633***	−322.89	5.707e−34***	−246.34	0.2371
0029	−34.7271	−49.3546	31.4312	−6.4931	0.1111	−4.2958	0.3384
0030	−0.9734***	−2.5813***	1.0175***	−186.55	3.269e−15***	−153.19	0.1788
0031	−1.0251***	−2.8574***	0.9995**	−174.66	4.070e−15***	−141.53	0.1897
0033	−0.351.	−2.8376***	0.6466*	−236.29	6.135e−21***	−189.75	0.1970
0035	−2.0108***	−3.6248***	1.1273.	−90.583	1.178e−07***	−74.629	0.1761
0036	−0.8412***	−1.731***	0.9482***	−209.86	2.693e−12***	−183.22	0.1269
0038	1.1026***	−2.9557***	1.3889***	−864.31	6.885e−185***	−440.26	0.4906
0039	−2.5414***	−5.3812.	0.958	−51.065	6.888e−05**	−41.482	0.1877
0040	1.4268***	−2.9466***	1.5597***	−1217.8	1.619e−306***	−513.68	0.5782
0041	−0.0546	−2.5515***	1.3091***	−387.74	5.094e−50***	−274.24	0.2927
0042	0.3258*	−2.6784***	1.154***	−456.71	2.258e−63***	−312.46	0.3158
0043	0.5003***	−6.502***	3.7658***	−4049.8	0.000***	−575.74	0.8578
0044	0.367**	−3.2201***	1.5226***	−571.35	1.881e−106***	−327.91	0.4261
0045	0.4726***	−2.3143***	1.1266***	−502.68	2.942e−65***	−354.09	0.2956
0046	−2.4884***	−6.3743.	0.3349	−38.663	0.001095*	−31.846	0.1763
0047	−1.2028***	−1.9968***	1.1046***	−178.61	1.877e−11***	−153.91	0.1383
0048	0.1808	−2.8057***	1.3427***	−460.43	1.085e−68***	−303.94	0.3399
0050	1.8282***	−3.0818***	1.6465***	−1810.6	0.000***	−632.89	0.6505
0051	−2.6132***	−3.6248*	1.5712.	−73.112	1.185e−06**	−59.467	0.1866
0052	0.0915	−2.2663***	1.105***	−397.08	3.357e−43***	−299.28	0.2463
0053	−4.0165***	−1.6	1.9091	−38.663	0.02527.	−34.985	0.09513
0054	−0.5786*	−3.4433***	1.5416***	−301.58	8.510e−44***	−202.41	0.3288
0057	−2.243***	−4.4925**	1.3417.	−80.946	3.935e−08***	−63.896	0.2106
0058	−1.7767***	−3.6248***	0.7683	−89.197	4.865e−07***	−74.661	0.1630
0060	−1.8591***	−3.8284***	1.2165*	−104.74	9.622e−10***	−83.977	0.1982
0061	−2.7633***	−2.9324**	1.8468*	−80.946	4.525e−07***	−66.338	0.1805
0062	−2.3016***	−2.7751***	1.884***	−115.63	5.058e−11***	−91.926	0.2050
0064	−1.8825***	−2.3123***	1.1071.	−108.72	1.025e−06**	−94.928	0.1268
0066	−0.7933***	−1.9523***	1.4694***	−272.02	1.770e−25***	−215.02	0.2095
0067	−2.2128***	−3.2262***	1.3075.	−87.711	3.949e−07***	−72.967	0.1681
0068	−3.7222***	−2.4349.	2.1972.	−51.065	0.0003792**	−43.188	0.1543
0069	−2.9135***	−2.7053*	1.5489.	−62.217	0.0001606**	−53.481	0.1404
0070	−5.5277*	−4.6093	3.4475	−24.418	0.003161*	−18.661	0.2358
0072	−2.4055***	−3.8442*	1.1669	−68.117	1.031e−05**	−56.635	0.1686
0074	−39.8527	−0.6931	35.7267	−6.4931	0.3211	−5.3571	0.1750
0075	−2.7733***	−5.1423	6.812e−16	−28.208	0.02119.	−24.354	0.1366

(*continued on next page*)

Table B.5 (*continued*).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR p-value:	Log-Likelihood:	Pseudo R-squ.:
0078	−3.1992***	−3.2262	0.5053	−28.208	0.07206	−25.578	0.09325
0080	−34.6479	−49.5334	31.352	−6.4931	0.1111	−4.2958	0.3384
0081	−5.4237*	−3.9835	3.0265	−20.427	0.01837.	−16.430	0.1957
0082	−2.585***	−2.4091**	1.8101**	−94.835	1.688e−07***	−79.241	0.1644
0083	−2.4587***	−3.053***	1.6682*	−90.296	6.709e−08***	−73.778	0.1829
0086	−2.6557***	−3.9835**	1.8468*	−80.253	1.490e−08***	−62.232	0.2246
0089	−3.6201***	−2.4707.	1.8636.	−45.047	0.002609*	−39.098	0.1321
0090	−5.1158***	6.1889***	−7.572e−11	−16.183	1.000	−256.53	−14.85
0092	−3.7604***	−4.6093	1.2803	−24.418	0.02842.	−20.857	0.1458
0093	−41.8712	−3.2262	39.3513	−16.183	0.01059.	−11.635	0.2810
0094	−6.7648***	−0.2185	4.5534.	−38.663	0.001253*	−31.980	0.1728
0095	−2.8624***	−67.6384	−1.0449	−16.183	0.02869.	−12.632	0.2194
0096	−2.5929***	−3.2262**	1.6682*	−80.253	3.907e−07***	−65.498	0.1839
0098	−2.233***	−6.9969.	0.2736	−45.740	0.0001519**	−36.948	0.1922
0102	−3.0643***	−2.1314*	1.7796*	−67.424	0.0001363**	−58.523	0.1320
0103	−2.7499***	−5.3034*	1.7796*	−67.424	5.723e−08***	−50.748	0.2473
0108	−2.6625***	−2.6097.	0.8848	−54.649	0.004405*	−49.224	0.09927
0109	−2.2009***	−4.1503*	0.7211	−62.217	5.328e−05**	−52.377	0.1582
0111	−34.7411	−49.1592	31.4452	−6.4931	0.1111	−4.2958	0.3384
0112	−2.1505***	−3.2262**	1.0449.	−80.253	5.774e−06**	−68.191	0.1503
0113	−5.7024*	−2.7751	3.4475	−24.418	0.01036.	−19.848	0.1872
0114	−1.3738***	−2.1423***	1.0996**	−155.38	3.910e−10***	−133.72	0.1394
0116	−3.9792***	−3.2262	1.6682	−28.208	0.02500.	−24.519	0.1308
0117	−5.2113*	−2.2491	1.6682	−11.600	0.3946	−10.670	0.08017
0118	−3.5519***	−2.7053*	2.3655*	−62.217	8.814e−06**	−50.578	0.1871
0119	−3.5641***	−2.5473*	2.8111***	−84.340	6.500e−09***	−65.488	0.2235
0120	−2.7302***	−3.6248	−8.348e−16	−31.830	0.03681.	−28.528	0.1037
0124	−0.6897***	−2.0016***	1.133***	−249.67	2.801e−19***	−206.95	0.1711
0125	−34.7243	−49.5251	31.4285	−6.4931	0.1111	−4.2958	0.3384
0126	−34.6694	−49.1533	31.3735	−6.4931	0.1111	−4.2958	0.3384
0127	−3.5683***	−2.8434*	2.4765*	−64.848	1.982e−06**	−51.717	0.2025
0128	−2.9269***	−2.4707*	1.8636*	−75.538	6.805e−06**	−63.640	0.1575
0130	−4.3944*	−58.791	−8.799e−16	−6.4931	0.3333	−5.3944	0.1692
0131	−0.492*	−2.5918***	0.9933***	−252.62	1.183e−23***	−199.83	0.2090
0134	−3.0673***	−4.6093.	1.2803	−41.905	0.0008074**	−34.783	0.1699
0135	−41.8751	−3.2262	39.3552	−16.183	0.01059.	−11.635	0.2810
0138	−4.3921***	−4.6093	2.1197	−24.418	0.01227.	−20.018	0.1802
0140	−2.3444***	−3.2262*	0.6092	−57.468	0.001213*	−50.753	0.1168
0141	−34.6479	−49.5334	31.352	−6.4931	0.1111	−4.2958	0.3384
0144	−34.7028	−49.5164	31.4069	−6.4931	0.1111	−4.2958	0.3384
0145	−60.4302	−2.2491	58.7576	−35.309	1.792e−05**	−24.379	0.3095
0146	−53.7961	−66.3303	51.1934	−11.600	0.01235.	−7.2054	0.3788
0147	−34.7303	−49.3017	31.4345	−6.4931	0.1111	−4.2958	0.3384
0149	−0.0345	−2.3743***	1.1957***	−383.90	2.460e−43***	−285.79	0.2556
0154	−1.5328***	−2.1129***	0.9527*	−128.85	1.802e−07***	−113.32	0.1205
0155	−4.7374***	−0.6931	1.0449	−16.183	0.6924	−15.816	0.02272
0156	−2.3368***	−2.2491*	0.9933	−74.844	0.0005050**	−67.254	0.1014
0160	−2.5384***	−2.6519*	1.1669	−67.424	0.0002503**	−59.131	0.1230
0162	−3.6777***	−1.0416	0.8848	−31.830	0.3734	−30.845	0.03095
0163	−53.796	−66.3303	51.1933	−11.600	0.01235.	−7.2054	0.3788
0164	−2.4279***	−1.7559**	1.7248***	−112.30	4.385e−07***	−97.662	0.1304
0165	−3.543***	−2.2491	−1.6682	−11.600	0.3946	−10.670	0.08017
0167	−4.7306***	−3.9835.	3.0265.	−35.309	0.0003375**	−27.315	0.2264
0168	−5.3919***	−1.1453	3.6267*	−45.047	0.0005172**	−37.480	0.1680
0169	−34.7268	−49.5517	31.431	−6.4931	0.1111	−4.2958	0.3384
0170	−52.6057	−3.9835	50.4464	−20.427	0.001561*	−13.965	0.3164
0172	−34.7145	−49.5562	31.4187	−6.4931	0.1111	−4.2958	0.3384
0173	−3.825***	−2.2491	1.6682	−35.309	0.02424.	−31.589	0.1054
0175	−4.3921***	−4.6093	2.1197	−24.418	0.01227.	−20.018	0.1802
0177	−34.6969	−49.5222	31.4011	−6.4931	0.1111	−4.2958	0.3384
0178	−4.0892***	−1.8351	1.2803	−24.418	0.1983	−22.800	0.06627
0182	−1.5682***	−2.5236**	0.1112	−87.018	0.0002151**	−78.574	0.09704

(*continued on next page*)

Table B.5 (*continued*).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR *p*-value:	Log-Likelihood:	Pseudo R-squ.:
0183	−2.3728***	−1.7784	−3.187e−16	−51.065	0.08403	−48.589	0.04850
0184	−2.8639***	−3.4311.	1.2246	−51.065	0.0006883**	−43.784	0.1426
0188	−1.7381***	−1.8796***	1.2518**	−134.49	6.030e−08***	−117.87	0.1236
0189	−0.5452*	−2.7053***	0.9407***	−242.89	6.420e−22***	−194.10	0.2009
0190	−53.796	−66.3303	51.1933	−11.600	0.01235.	−7.2054	0.3788
0192	−3.1162***	−2.6769.	1.3417	−48.098	0.003528*	−42.451	0.1174
0193	−0.8028***	−2.4129***	0.8051*	−193.56	5.986e−14***	−163.11	0.1573
0195	−4.9914*	−65.6951	2.4765	−16.183	0.01227.	−11.783	0.2719
0196	−53.796	−66.3303	51.1933	−11.600	0.01235.	−7.2054	0.3788
0197	−0.4724*	−1.8984***	0.4482	−220.60	2.335e−11***	−196.12	0.1110
0198	−2.2949***	−4.6093.	−3.384e−16	−41.905	0.002786*	−36.022	0.1404
0199	−3.4398***	−3.4969.	1.6682	−41.905	0.001472*	−35.383	0.1556
0200	−5.2113*	−2.2491	1.6682	−11.600	0.3946	−10.670	0.08017
0202	−65.49	−53.0811	63.2928	−16.183	0.001372*	−9.5917	0.4073
0203	−1.0687***	−2.5437***	0.6199	−145.98	1.348e−09***	−125.56	0.1399
0204	−1.6845***	−2.6472***	1.6682***	−156.03	2.036e−15***	−122.20	0.2168
0205	−1.8753***	−1.9199***	1.2803**	−120.89	2.531e−07***	−105.70	0.1257

Table B.6
Estimated model parameters for INST03. (significance levels: '.' 0.05; '*' 0.01; '**' 0.005; '***' 0.001).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR *p*-value:	Log-Likelihood:	Pseudo R-squ.:
0001	0.6081***	−2.5638***	1.7185***	−800.58	9.161e−153***	−450.50	0.4373
0002	0.0878	−2.319***	1.5743***	−530.95	4.554e−74***	−362.07	0.3181
0004	−0.65***	−2.1168***	1.7096***	−362.67	2.347e−40***	−271.42	0.2516
0005	−4.5667***	−2.7751	2.1197	−24.418	0.04022.	−21.205	0.1316
0006	2.3272***	−2.4729***	1.7002***	−3132.6	0.000***	−1247.1	0.6019
0007	−1.6158***	−1.4869***	1.3464***	−169.79	7.428e−09***	−151.07	0.1102
0008	−5.3562***	1.2589	1.2803	−25.111	0.2687	−23.797	0.05234
0009	0.0856	−3.4385***	1.3137***	−468.67	7.707e−67***	−316.44	0.3248
0010	−1.3722***	−1.9448*	−0.4319	−89.197	0.001462*	−82.669	0.07318
0011	1.6868***	−2.5779***	1.6996***	−1828.9	0.000***	−819.09	0.5521
0012	−2.3432***	−0.6931	0.8524	−93.420	0.06303	−90.656	0.02959
0013	−2.1625***	−0.9601	−2.4765.	−38.663	0.01974.	−34.737	0.1015
0015	−1.37***	−2.0688***	1.0262*	−158.72	3.240e−09***	−139.17	0.1232
0016	0.215	−2.304***	1.2803***	−511.76	7.535e−60***	−375.62	0.2660
0017	−3.5709***	0.9062	−5.901e−16	−45.047	0.4456	−44.238	0.01794
0018	−3.2442***	−2.7209*	2.3073**	−78.716	3.587e−07***	−63.875	0.1885
0019	−42.0326	1.2589	37.631	−11.600	0.08415	−9.1246	0.2134
0020	2.8733***	−2.5235***	1.6463***	−4911.0	0.000***	−1825.8	0.6282
0021	1.0258***	−2.6674***	1.7985***	−1179.5	1.697e−257***	−588.31	0.5012
0022	−1.2023***	−0.8334***	1.4884***	−262.74	3.229e−13***	−233.98	0.1095
0023	−1.0953***	−1.5889***	1.2081***	−219.59	1.648e−12***	−192.46	0.1236
0024	−3.4106***	−3.2262.	1.4467	−38.663	0.005833*	−33.518	0.1331
0026	−2.7189***	−2.4707.	0.5524	−45.047	0.02702.	−41.436	0.08016
0027	0.0717	−2.2491***	1.4274***	−519.96	1.189e−60***	−381.98	0.2654
0028	−2.7733***	−5.1423	−2.969e−16	−28.208	0.02119.	−24.354	0.1366
0029	−3.0429***	−1.8351	−0.6092	−24.418	0.3166	−23.268	0.04710
0030	0.1642	−2.5158***	1.2446***	−458.77	1.926e−57***	−328.18	0.2847
0033	−1.2803***	−1.8831***	0.8848*	−162.14	4.141e−08***	−145.14	0.1048
0034	−1.0301***	−1.5759***	0.9833***	−207.76	4.558e−10***	−186.25	0.1035
0035	−3.488***	−0.5335	1.3863	−55.342	0.09826	−53.022	0.04192
0036	−3.2039***	−2.2491	0.7683	−37.101	0.08043	−34.580	0.06793
0037	−3.2958**	−83.0849	−50.1306	−6.4931	0.1111	−4.2958	0.3384
0038	−1.3253***	−2.2827***	1.1967***	−175.22	3.430e−12***	−148.83	0.1507
0039	−0.4957*	−2.2696***	0.6763*	−236.09	7.680e−16***	−201.29	0.1474
0040	−0.6079**	−1.7807***	0.8348***	−243.22	8.663e−14***	−213.14	0.1237
0041	−1.6323***	−1.4113***	1.2336***	−155.41	2.132e−07***	−140.05	0.09884
0042	−0.6553***	−1.9584***	0.9995***	−269.25	6.368e−17***	−231.96	0.1385

(*continued on next page*)

Table B.6 (*continued*).

Stop	Intercept	Batt.	Cons.	LL-Null:	LLR *p*-value:	Log-Likelihood:	Pseudo R-squ.:
0043	0.1382	−2.5608***	1.1254***	−452.48	8.487e−50***	−339.49	0.2497
0044	−0.6507***	−1.9719***	1.2359***	−281.53	2.498e−22***	−231.79	0.1767
0045	−4.3137***	−0.9096	2.3073.	−45.740	0.01317.	−41.410	0.09466
0046	−2.7673***	−1.7784	0.7066	−51.759	0.04973.	−48.757	0.05798
0047	0.3238*	−1.6767***	1.2347***	−513.78	9.860e−53***	−394.03	0.2331
0048	−1.6366***	−1.3933*	0.5939	−118.93	0.001537*	−112.45	0.05447
0049	0.2522.	−1.8317***	1.4575***	−602.71	5.057e−68***	−447.76	0.2571
0050	−4.126***	−0.6931	−1.893e−16	−16.183	0.8939	−16.071	0.006932
0051	−0.7401***	−2.1197***	1.4744***	−301.61	4.779e−28***	−238.70	0.2086
0052	−0.6131***	−1.4085***	1.1382***	−296.33	6.587e−17***	−259.07	0.1257
0053	0.2624.	−1.9785***	1.7699***	−736.07	3.093e−104***	−497.73	0.3238
0054	−0.269	−2.316***	1.0189***	−326.90	4.597e−28***	−263.96	0.1926
0055	1.0646***	−2.7573***	1.6095***	−1060.3	2.325e−219***	−556.85	0.4748
0056	0.6398***	−2.39***	1.5225***	−774.95	2.479e−122***	−494.94	0.3613
0057	−0.2371	−2.1884***	1.0388***	−328.24	1.697e−28***	−264.30	0.1948
0058	0.3448*	−2.854***	1.8948***	−752.36	3.949e−149***	−410.65	0.4542
0059	−3.2958**	−83.0849	−50.1306	−6.4931	0.1111	−4.2958	0.3384
0060	−1.0499***	−1.7438***	1.3528***	−237.70	2.260e−16***	−201.67	0.1516
0061	−1.7988***	−0.7635	0.1821	−101.66	0.2085	−100.09	0.01542
0062	−2.6237***	−1.8351	−6.659e−16	−41.905	0.1356	−39.907	0.04767
0063	−0.1218	−1.552***	0.9806***	−356.55	1.469e−23***	−303.97	0.1475
0064	−3.9605***	−0.9096	1.8636.	−45.740	0.03724.	−42.450	0.07194
0065	−1.2696***	−2.4624***	0.8683.	−151.96	1.093e−09***	−131.32	0.1358
0066	−1.6863***	−2.2007***	1.1433*	−135.14	4.404e−08***	−118.20	0.1253
0067	−0.7534***	−1.0543***	1.3347***	−287.77	4.590e−17***	−250.15	0.1307
0070	−0.323.	−2.0922***	1.7127***	−412.75	1.239e−55***	−286.32	0.3063
0071	−1.3341***	−1.9775***	1.4615***	−196.41	4.359e−15***	−163.34	0.1684
0072	0.5318***	−2.4617***	1.3226***	−643.30	5.664e−89***	−440.10	0.3159
0073	−2.6925***	−1.3993*	1.9642***	−116.68	5.653e−07***	−102.30	0.1233
0074	−4.2866***	0.6235	0.5053	−28.208	0.7154	−27.873	0.01187
0075	−1.5512***	−0.9262.	0.22	−118.52	0.06232	−115.75	0.02342
0076	−0.4049.	−1.8738***	1.2617***	−331.43	2.141e−28***	−267.71	0.1922
0077	−3.8692***	−0.448	2.1754*	−66.235	0.003151*	−60.475	0.08696
0078	−2.0661***	−1.4916*	0.8224	−94.835	0.002589*	−88.879	0.06281
0079	−0.2322	−1.9505***	1.0678***	−341.88	2.004e−27***	−280.41	0.1798
0080	−3.1288***	−2.2491	−0.7683	−20.427	0.2836	−19.167	0.06169
0081	−1.3377***	−2.369***	1.7318***	−219.09	4.159e−22***	−169.86	0.2247
0082	−0.6776**	−2.2491***	0.7015*	−218.95	1.529e−13***	−189.44	0.1348
0083	−1.3268***	−2.1831***	1.7293***	−235.98	1.344e−21***	−187.92	0.2037
0084	−0.6913***	−1.8569***	1.171***	−264.96	3.214e−19***	−222.37	0.1607
0085	−0.5441*	−1.4869***	0.7804***	−249.41	6.164e−12***	−223.60	0.1035
0086	−0.4509.	−2.316***	0.4906.	−229.96	2.515e−14***	−198.65	0.1362
0087	−2.4035***	−2.7053***	1.793***	−105.84	4.858e−09***	−86.695	0.1809
0088	−2.3803***	−2.0085.	0.6794	−64.848	0.008387*	−60.067	0.07373

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