Optimizing the positions of battery swapping stations - Pilot studies and layout optimization algorithm

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Optimizing the positions of battery swapping stations

- Pilot studies and layout optimization algorithm -

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ABSTRACT: For electric scooters, battery swapping is a promising alternative to battery charging due to the lower weight and volume of their batteries that allows a manual replacement at battery swapping stations. Mobile batteries are shared between all users and the target of the operator is therefore to maximize the customer satisfaction while minimizing system set-up and operation costs. Here we give an overview of Honda's activities for a Battery as a Service (BaaS) business in Indonesia, Philippines and India, while looking specifically at the optimal placement of battery swapping stations with a given customer demand. Multiple objectives like set-up cost, energy costs, and customer detours are considered. We employ a Large Neighborhood Search (LNS) approach that uses specific destroy and repair operators for each objective and includes a Mixed Integer Linear Programming (MILP) element for repairing solutions. Our results show that the employed LNS outperforms a state-of-the-art pure MILP approach for larger problem sizes with up to 500 potential station locations and 1000 trips. Overall 10-30% better results compared to standard approaches can be obtained.

KEY WORDS: Battery as a Service, Layout Optimization, Mixed Integer Linear Programming, Large Neighborhood Search

1. INTRODUCTION

One of the main challenges for the wider adoption of electric mobility is the limited range and long recharging times of electric vehicles. For smaller vehicles like scooters, however, batteries can be small and light-weighted enough, to allow for a manual replacement of depleted batteries by fully-charged ones, instead of charging these batteries at charging stations, which often takes hours. A mobility service would need to provide a pool of shared portable batteries that customers can exchange at battery swapping stations (BSS).

One major cost factor is the number of required batteries and BSS to provide a high service level. In this work we focus on optimizing the number, location (placement), and dimensioning of BSSs in order to provide maximum service quality, as well as minimizing the setup and operation costs of the BSS system. The optimization goals are combined in a linear fashion with different weights, yielding the total objective function to be optimized.

Such problems are typically approached by first collecting information about expected customer demand, for example in the form of O/D (origin-destination) pairs, representing typical routes people use in their daily lives. This data can be derived from various sources like customer surveys, traffic monitoring, or city census data. Another approach (3) is to directly ask potential users to rate possible service station locations. In this work we assume O/D pairs to be given.

Then, based on the collected data, the placement of BSS is determined. Typically, the system operator wants to install a certain number of BSS given a larger number of potential candidate locations considering installation costs, maintenance costs and customer satisfaction (e.g., minimizing the detours customers need to take to reach the next BSS). The problem is therefore a combinatorial optimization problem, similar in structure to other problems in Operations Research. Interestingly many fleet-management and EV charging algorithms fall into the same category. For solving this type of problem, very efficient algorithms (like Mixed Integer Linear Programming, MILP) exist that can find the optimal solution, in our case the best selection of BSS locations to optimize the given cost and customer satisfaction function. A severe problem, however, is the computational scaling of these approaches. Algorithm runtime and computer memory requirements grow quickly with the size of the business (station locations, number of BSS, and considered O/D pairs). For larger businesses with 1000s of BSS (or even more) other approaches are needed, that trade optimality for lower run-time.

In this article we employ a heuristic algorithm, a Large Neighborhood Search (LNS) for this task. For each of the optimization goals (minimizing system set-up and operation costs and maximizing service quality) we design specific destroy and repair operators (elements of the LNS algorithm) with which the LNS generates optimized solutions.

We report results for artificial data (test instances can be downloaded from [1]) generated by adopting approaches from literature, but for the real service described below obviously various other sources have been used, based on availability.

2. BaaS in Indonesia, Philippines, India and Japan

2.1. Battery as a Service (BaaS)

South and south-east Asia are two world regions with a large and quickly growing mobility demand based on light vehicles like scooters, commuter motorcycles and rickshaws. Electrification of this market is essential to reach global climate protection goals and to improve local air quality. Therefore, each country has begun to impose regulations to reduce CO_2 emissions. For example, Indonesia is facing the problem of air pollution caused by increased traffic, and in 2012 it tightened its motorcycle emission regulations. On the other hand, international greenhouse gas emission standards, such as the Greenhouse Gas Protocol formulated mainly by WBCSD (World Business Council for Sustainable Development) and WRI (World Resources Institute), have recently been established. In such a situation, Honda's aim is to make 100 percent of automobile sales battery-electric vehicles (EVs) and fuel cell electric vehicles (FCVs) by 2040.

In addition to electric vehicles also a convenient, clean, affordable, and scalable battery charging solution is required, for which BaaS is a proposed solution. In the BaaS provided by Honda, users can visit the nearest BSS when the battery level is low, remove the used battery from the vehicle, insert it into the BSS, and immediately receive a charged battery. This would allow users to drive continuously without worrying about recharging time, and with BSS being installed throughout the city, they would not have to worry about cruising distance. Furthermore, if batteries can be shared, for example by using them in other devices when the vehicle is not in use, or mass production can be achieved by unifying battery standards, battery costs could be reduced. Moreover, combining renewable energy and communication technologies to manage electric vehicles use and battery recharging could lead to cleaner and more efficient mobility.

2.2. Pilot project and Main project

Honda had conducted BaaS pilot project in Indonesia (a project subsidized by NEDO), Philippines (a project subsidized by the Japanese Ministry of the Environment) and India. We have had motorcycles (2-wheel) and rickshaws (3-wheel) used for personal use (B2C) and mail, food delivery, and taxies (B2B) to identify issues and verify business feasibility. The battery packs that have been used in the pilot project can store data while driving. We constructed a system that, when a battery is inserted into the BSS (Figure 1), this data is transmitted to the cloud together with information on the BSS. By analyzing this data, we have been studying and verifying the demand for swapping, the user experience, and what kind of use is expected.

Figure 1: BSS (Honda Mobile Power Pack Exchanger) used in the pilot project[2]

[1] https://www.ac.tuwien.ac.at/research/problem-instances/#Battery_Swapping_Station_Location_Problem_BSSLP

[2] https://www.honda.co.jp/environment/hoteyes/hoteyes233.html

Figure 2: BSS and electric scooters in the Philippines[3].

Honda has developed the battery pack "Honda Mobile Power Pack e:" (Figure 3) and BSS "Honda Power Pack Exchanger e:" (Figure 4) based on the knowledge gained from these pilot projects. Honda established HEID (Honda Power Pack Energy India[4]), a local subsidiary in India for the purpose of BaaS business, installed Honda Power Pack Exchanger e: in the city of Bengaluru, and provides sharing services for Honda Mobile Power Pack e:. In cooperation with rickshaw manufacturers, we plan to begin operations in a limited number of cities and gradually expand to other areas. In addition, we plan to launch BaaS business using these products in other countries including Japan.

<Specifications of Honda Mobile Power Pack e:>	
External dimensions (mm)	Approx. 298×177.3×156.3
Battery type	Lithium-ion battery
Rated voltage	Approx. 50.26V
Rated capacity	26.1Ah/1314Wh
Weight	10.3kg
Charging time	Approx. 5 hours

Figure 3: Key features of Honda Mobile Power Pack e:[5]

Product name		Control Unit (C-BEX)	Extension Unit (Ex-BEX)
Compatible battery		Honda Mobile Power Pack e:	
Frequency (Hz)		50/60	
Rated power consumption (kW)		6.5	
Weight (kg)		361	360
External dimensions (mm)	W × H × D	960 × 1,820 × 758	
Connecting power supply (V)		Japan model: 3-phase 2-wire 200 India model: 3-phase 4-wire 400	
Cooler		○	○
Monitor		○	–
communication function		○	–
NFC authentication device		○	–

Figure 4: Key features of Honda Power Pack Exchanger e:[6]

2.3. Challenges of BaaS

The demand distribution of swaps actually obtained in the pilot project is shown in the Figure 5. This is the actual swapping in Romblon Island in the Philippines. The swapping is concentrated in some BSS, indicating that the frequency of use is highly unbalanced. This unbalanced frequency of use was not limited to Romblon Island but was observed in all regions. Since a small number of BSS are sufficient for locations that are used infrequently, asset costs can be reduced by reducing the number of installations in such locations. On the other hand, in developing a sharing business, it is important that a sufficient number of BSS are installed throughout the city and that users can access them when they want to swap. Therefore, it is necessary to provide a number of BSS and convenient station locations that meet demand.

In order to minimize the number of assets without compromising user convenience, it is desirable to equalize the number of swaps by layout optimization

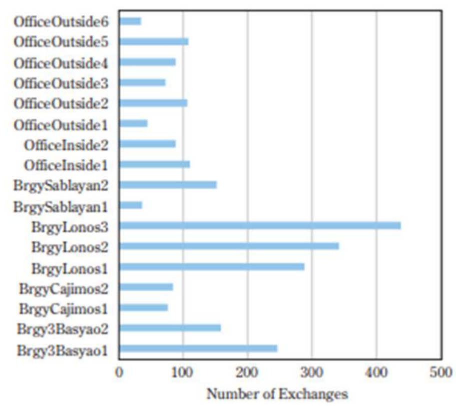

Figure 5: Number of swaps per BSS in a month in the Philippines.[7]

3. Layout Optimization Algorithm

The problem we address is the optimal placement of a service stations in a defined area aiming to maximize user satisfaction and minimizing operational costs. This problem can be expressed and solved as a mixed integer linear programming (MILP) problem. MILP solvers usually perform well for hard problem instances up to a certain size, but for larger problem sizes the time needed to find an optimal solution exceeds any acceptable limit and the performance

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3 https://www.honda.co.jp/environment/hoteyes/hoteyes233.html
4 https://www.honda-mpp.com/in/
5 https://global.honda/newsroom/news/2021/c211029beng.html
6 https://global.honda/newsroom/news/2022/p221025eng.html

7 "Development of Honda Mobile Power Pack and Demonstration Projects for the Battery", Society of Automotive Engineers of Japan, Vol. 74, No. 2, 2020

deteriorates quickly after a certain point. Even with careful problem formulation and the usage of state-of-the-art solvers[8] relevant problem sizes cannot be handled in an acceptable amount of time. While this is not a problem for pilot studies, it becomes critical for any reasonable real-world business.

We therefore employ heuristic methods to find approximate solutions for larger problem instances, more specifically, a Large Neighborhood Search (LNS) hybridized with a MILP approach is applied.

Large Neighborhood Search (5) is a prominent metaheuristic for addressing difficult combinatorial optimization problems, which builds upon effective lower-level heuristics.

A basic LNS in essence follows a classical local search framework, but much larger neighborhoods (in search space) are considered in each iteration. The key-idea is to search these neighborhoods not in a naive enumerative way but to apply some more efficient problem-specific procedure to solve the subproblem induced by each neighborhood in order to obtain the best or a promising heuristic solution from the neighborhood.

Our LNS follows a so-called destroy and repair scheme: A current incumbent solution is partially destroyed, typically by freeing a subset of the decision variables and fixing the others to their current values, and then repaired again by finding best or at least promising values for the freed variables.

Figure 6: Basic LNS procedure.

Figure 6 shows a visualization of this procedure. The LNS proposed in this article removes in each of its iterations a set $L_{\text{destroy}}(x)$ of the BSS from the current solution x and then repairs the solution by solving a MILP that considers not all available stations but only a small, promising set of candidate stations L_{repair}. Note that destroy and repair schemes do not refer to real world operations, but only virtual operations inside the optimization algorithm while searching for the best possible solution.

For each optimization goal specific destroy and repair operators are designed that decide which stations should be contained in $L_{\text{destroy}}(x)$ and L_{repair}.

The destroy operators remove stations from the current solution that are the least important with respect to their respective optimization goal. The repair operators select the stations that are most likely to improve the respective optimization goal when added to the solution.

The operators are combined in one of two ways: Each operator can either be chosen uniformly at *random* in each LNS iteration, or all operators are combined in a linear fashion (*mixed*) to select the most promising stations with respect to all optimization goals. For further details on the destroy and repair operators we refer to (6).

4. RESULTS

We test our LNS on artificial instances generated by adopting approaches from literature (1,2) . We consider six groups of instances with a different number of possible station locations n and O/D pairs m. Each group contains 30 instances. For details on how the instances were generated, see (6).

The proposed LNS was implemented in Julia 1.6 using Gurobi 9.1 as underlying MILP solver. All test runs have been executed on an Intel Xeon E5-2640 v4 2.40GHz machine in single-threaded mode with a global time limit of one hour per run.

On each instance, we test three different weight configurations (α_{setup} , $\alpha_{operation}$, $\alpha_{service}$) for combining the optimization goals (setup and operation costs as well as service quality) in a linear fashion. Specifically, we set α_{setup}, $\alpha_{operation}$ to 0.01 and test different values for $\alpha_{service} \in \{0.1, 1, 10\}$. Therefore, in the remainder of this section a configuration will be indicated by $\alpha_{service}$ only. Effectively, $\alpha_{service}$ specifies the relative importance of service level relative to setup and operation costs.

For the LNS the size of $L_{\text{destroy}}(x)$ and L_{repair} was set to five for all experiments.

The quality of solutions is evaluated in terms of optimality gaps to the best lower bounds obtained by trying to solve the problem as a MILP within a time limit of one hour. A gap value of zero means that an optimal solution was found, while larger gaps mean

[8] https://www.gurobi.com

that that there should be better solutions in terms of cost and service level that could not be identified.

Figures 7-9 compare the performance of the LNS to other approaches for different values of $\alpha_{service}$. Two LNS variants are considered here. The variant "*random*" applies in each iteration one of the destroy and repair operators chosen uniformly at random (so the approach is random only for the selection of the specific operator in each iteration of the search.). The variant "*mixed*" combines all the proposed operators in a linearly weighted fashion using the weights α_{setup}, $\alpha_{operation}$, and $\alpha_{service}$.

The LNS variants are compared to solutions generated by the initial construction heuristic, denoted by CH, as well as solutions obtained by Gurobi within one hour, denoted by MILP.

The initial construction heuristic generates a solution by first solving the LP relaxation of the problem and then repairing the solution afterwards. More specifically, we generate a solution under the assumption that the number of stations and their number of battery-exchange modules is continuous instead of integer. Such a relaxed problem can in general be solved faster than the original problem with integral variable domains. To eventually transform the solution to the relaxed problem into a feasible solution, the basic idea is to round up all fractional values. However, there might be a limit on the number of stations and battery-exchange modules that can be built and naively rounding up all fractional values might result in an infeasible solution. To overcome this issue, care is taken to not exceed these limits and some values are thus rounded down instead of up to ultimately guarantee feasibility. Afterwards, the assignment of customer demand to the stations is recalculated based on the solution obtained after rounding. For a more detailed description of this procedure see (6).

Starting from instances with n=200 and m=400, both LNS variants are able to consistently achieve superior results with up to 29% lower objective values than those obtained by the MILP approach. Moreover, we can see that the LNS strongly improves the initial solution obtained by the construction heuristic.

The state-of-art MILP approach finds (near) optimal solutions for small problem instances (business sizes) but falls behind even simple heuristics (like CH) for larger problems sizes.

Optimality gaps generally increase with growing instance size and growing $\alpha_{service}$ value for the tested LNS variants. For $\alpha_{service} = 0.1$, the mixed variant performs slightly better than the random variation.

For $\alpha_{service} = 10$ (very strong weight on providing a high service quality) the mixed strategy can obtain results up to 3% better on average than the random strategy.

We performed one-sided Wilcoxon signed-rank tests between the solutions obtained by the two LNS variants.

For almost all instance groups and values of $\alpha_{service}$, the mixed strategy achieved statistically significantly better results than the random strategy within a 95% confidence interval.

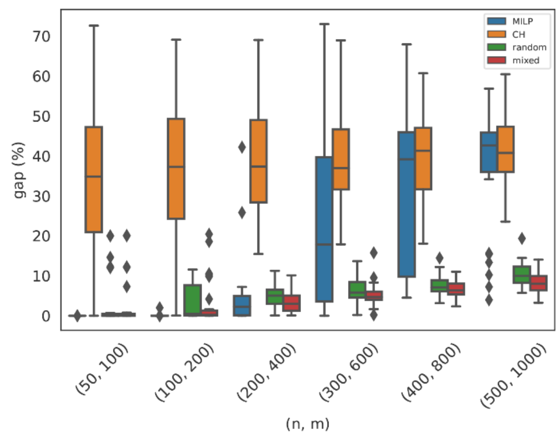

Figure 7: Comparison of the LNS variations to other approaches with $\alpha_{service} = 0.01$

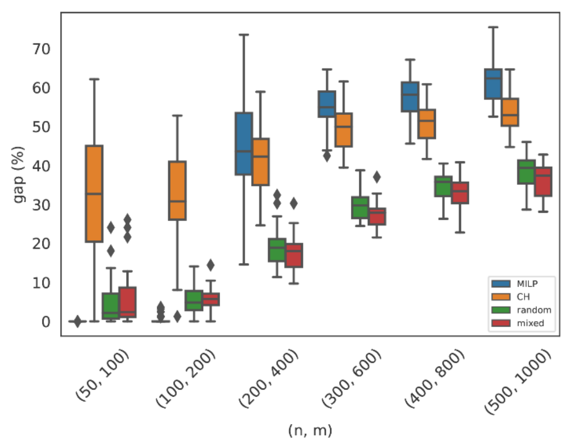

Figure 8: *Comparison of the LNS variants to other approaches with* $\alpha_{service} = 1.0$.

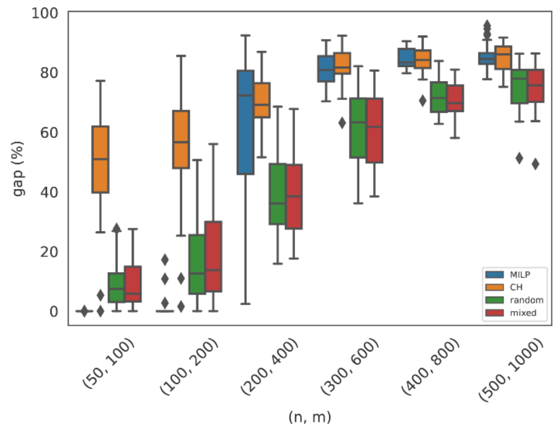

Figure 9: Comparison of the LNS variants to other approaches with $\alpha_{service} = 10.0$.

5. CONCLUSION

Battery as a Service (BaaS) is a promising approach for de-carbonizing light vehicles. A key challenge for this type of system is deciding on the best number and placement of battery swapping stations (BSS) to minimize set-up costs and maximize customer satisfaction.

Problems of this type are typically solved using MILP-based approaches, that, however, become computationally infeasible beyond a few hundred potential station locations and considered customer routes. Using a metaheuristic approach (LNS) we could show that problems with 500 locations and 1000 O/D pairs can be solved with good performance. Compared to a state-of-art MILP approach the solution quality, a combination of installation & operation costs and customer satisfaction, can be improved by up to almost 30%.

We are currently investigating a multi-level optimization approach for handling even larger problem sizes, that scales to problems up to two orders of magnitude larger (4). This approach works by first merging locations and O/D pairs on a coarser resolution multiple times until it can be solved with exact or heuristic approaches and then projecting the solution back to the original resolution.

Using computational methods for optimizing the system layout can be a very efficient and low cost approach to substantially reduce costs while at the same time providing a high service quality to customers. Honda's BaaS business in India determined the installation location based on the optimized installation location obtained by this method, and in the future, the effectiveness of this method will be verified through the data collected in the project.

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