TECHNICAL UNIVERSITY OF MUNICH

Quantum Entrepreneurship Lab

Final Report - ChargeQ

Viviana Sutedjo, Philipp Krüger, Katharina Kircher, Maximilian Huber, Florian Burger

Semester:	Winter 2020/21
Submission Date:	March 23, 2021

Contents

Chapter 1

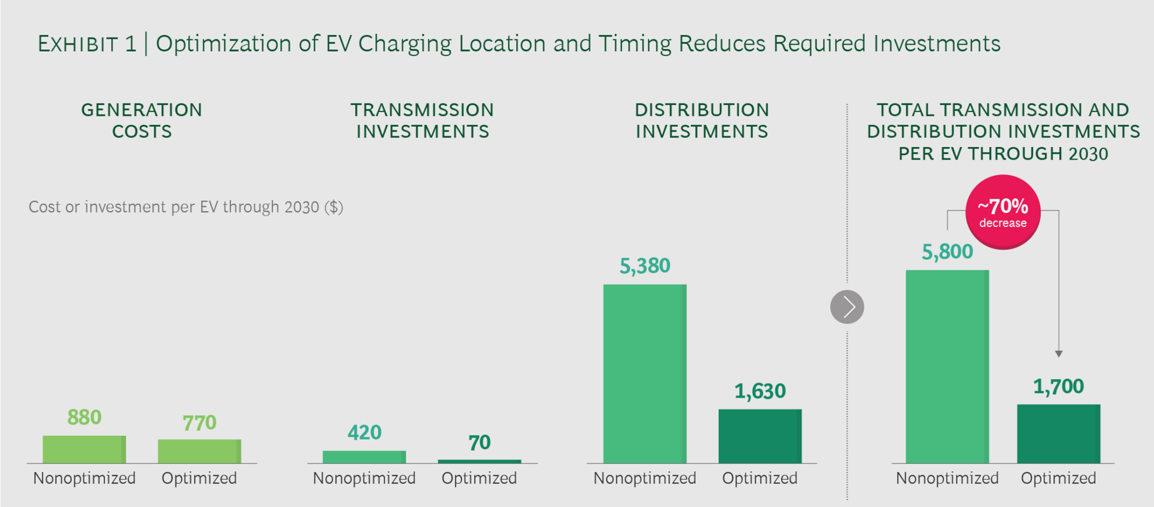
Business

1.1 Problem and Solution Scope

Modern cities are facing the well-known problems of environmental air pollution, forcing the adoption of new strategies for mitigating greenhouse gas emissions. Some of the actions for alleviating such emissions are evolving around electric vehicles (EVs). Increased regulatory pressures and incentives are fueling the widespread adoption of EVs in Germany. According to Statista the number of EVs rose from 83.175 in 2019 to 136.617 in 2020 - this represents a growth of 65%[1]. There is no denying anymore that EVs are going mainstream. The consulting company BCG expects that, by 2030, EVs (mild and full hybrids, plug-in hybrids, and battery EVs) will account for 50% to 60% of global new-car sales. This development will have a profound impact on the energy demand. If managed incorrectly, these new types of consumption can put a significant pressure on the cities' grids, for instance by increasing the evening peak load[2]. Alexander Kunz, project manager at the German charging station manufacturer Wirelane, told us in an exclusive interview that it will require immense investments into the grid infrastructure to enable widespread adoption of EVs in German cities[3]. In a recent case study, BCG analyzed the impact of EVs on the grid in terms of additional generation, transmission and distribution investments. Transmission costs include transmission lines and substations. Distribution costs include distribution substations, transformers, circuits, and switches. They concluded that the timing - off-peak or peak hours - and location of EV charging tremendously influences the upfront investment by utility companies. As Exhibit 1 highlights, depending on charging patterns of the customer, utility companies can reduce their investments in grid upgrades per EV from 5,800 USD to 1,700 USD [4].

To understand why, imagine a local grid with 120 kW capacity. This grid could serve roundabout 40 households with each 3 kW of electricity use. Charging stations for home-use require between 3,7 kW to 22 kW of electricity for more powerful stations. Hence, the local grids will be the first constraint for widespread EV adoption. A potential solution to this problem is to let the households communicate with each other such that the EVs will be charged within different periods and the overall capacity of the local grid will not be overloaded. This technology is called vehicle-to-grid (V2G) and we differ in two levels of sophistication: unidirectional and bidirectional. Unidirectional charge poles are units that can only charge the battery of the car, thus no energy can be delivered back to the network. However, by varying the time of charging or the charge rate in case needs from the grid arise, they can assist in stabilizing the network. They are often referred to as unidirectional V2G, or V1G. Bidirectional charge poles are charge units that can be used to charge and discharge an EV's battery. That's why, next to their conventional use of charging the vehicle's battery, they are able to draw charged energy from the battery and inject it back into the grid. This service is called bidirectional V2G, or simply V2G. In case the energy is delivered to a household, a load, or any other consumer, the general term vehicle-to-anything or V2X is used. Besides the hardware, this technology also requires algorithms to determine the best suitable order to charge the different vehicles keeping in mind the total capacity, the routines of the people and in future also the dynamic energy prices. This problem has such a complexity, that quantum algorithms present a great opportunity to solve them at the required speed. We at ChargeQ are aiming to provide this software to make electric mobility a reality.

[1] https://de.statista.com/statistik/daten/studie/265995/umfrage/anzahl-der-elektroautos-in-deutschland/ (Dec 18, 2020)
[2] https://www.bcg.com/de-de/publications/2019/costs-revving-up-the-grid-for-electric-vehicles (Dec 18, 2020)
[3] Expert Interview with Alexander Kunz via Zoom on Dec 18, 2020
[4] https://www.bcg.com/de-de/publications/2019/costs-revving-up-the-grid-for-electric-vehicles (Dec 18, 2020)



Source: BCG analysis.
Note: For both charging patterns, we assume 15% EV penetration in 2030. The nonoptimized pattern assumes that 50% of charging occurs during peak hours, 25% in off-peak hours, and 25% in shoulder hours, and that a large share of charging occurs where grid capacity is constrained. The optimized charging pattern assumes that 50% of charging occurs during off-peak hours and 50% in shoulder hours, and that a small share of charging occurs where grid capacity is constrained.

Figure 1.1: Investments based on EV Charging Location and Timing

1.2 Target Customer

Utility companies maintaining local grids suffer most from the widespread adoption of EVs as they have to undertake huge infrastructure investments. To better understand who exactly we target, we will first briefly describe the different actors in the German electricity grid. Germany has a well developed and extensive electricity grid (Exhibit 2). It consists of the transmission grid – in which the power is transported at very high voltages – and distribution grids, which are used to supply local regions and end consumers with electricity. There are four transmission system operators in Germany (TenneT, 50Hertz Transmission, Amprion and TransnetBW), which facilitate the transport of electricity over large distances - with a minimum of loss, and directly to the areas where the power is consumed. In the case of alternating current (AC), electricity is transmitted with a maximum voltage of 220 kilovolts (kV) or 380 kV. At the level of the distribution grids the electricity is transmitted at high (60 kV to 220 kV), medium (6 kV to 60 kV) and low voltage (230 V or 400 V). Lower voltage grids distribute the power to end users. There are 883 regional and municipal distribution system operators (DSO) in this sector. All of them are potential customers. As our business model is based on B2B we are aiming to reach our customers via active acquisition based on network and cold calling. We want to leverage the network of our partners who offer charging stations to get referrals to DSOs.

Besides the paying customers, we also have users. These are the EV owners, which use our app to communicate with the charging station. We will reach this customer group through a cooperation with the charging station providers.

1.3 Value Proposition

ChargeQ offers the only platform that uses quantum computing to provide solutions for managing the load on power grids from high-performance electric car charging systems.

ChargeQ solves the energy supply problem with its communication, control and information platform that provides intelligent charging management for wallboxes and charging stations for EVs. The algorithm calculates the most favorable sequence of charging processes, taking into account customer preferences, and generates individual suggestions based on charging patterns. Scheduling problems are a subset of complex optimization problems where normal algorithms reach their limits. That's why we solve this problem with quantum computing![5]

Currently, most DSOs are not able to track the power consumption of the connected households and charging stations and thus cannot intervene. ChargeQ's charging management therefore helps to avoid the uneconomic peaks and at the same time guarantee a smooth charging process for the end customer - win win.

Our solution has three central aims: Prevention of electricity peaks, cost-savings for DSOs and combating climate change through accelerating EV adoption.

[5] The exact advantages of QC compared to normal algorithms are explained in detail in the technical part.

1.4 Target Market

For the analysis of the target market we use three key figures - TAM, SAM and SOM. TAM, i.e. Total Available Market, represents the total demand for a service or product. SAM, i.e. Serviceable Available Market, describes the share of the TAM that can be offered by the company's own product. In other words, it is the share of total demand that can potentially be met by the product offered. SOM (Serviceable Obtainable Market) is the part of the SAM that can actually be achieved in the near future.

In the case of ChargeQ, the total number of all private and public charging points in Germany is the TAM. There are currently 24,000[6] public charging points in Germany. However, a study by Capgemini assumes that these only account for 10% of the total charging points[7]. Conservatively, one can then assume a current market of 200,000 charging points in 2020 in Germany. For ChargeQ, the German state of Bavaria represents the SAM and thus public 3,600 charging points or a total of approximately 30,000 charging points. Bavaria and also Munich each represent the front-runner in terms of charging points nationwide. This is one reason why Munich is the first major city for ChargeQ to be the SOM, with 1,103 public charging points and thus approximately 10,000 charging points in total. There are two DSOs in Munich - SWM and Bayernwerk. The goal is to cover a market share of 50% with one. At an average price of €10 per month and charging point, this would mean an annual turnover of €600.000.

The growth opportunities of this market are immense. Capgemini expects in its study 2.5 - 3.8 million charging points by 2025, i.e. more than a tenfold increase. The German government also has ambitious goals and is aiming for one million public charging points by 2030, which matches the extrapolated figures from Capgemini and would result in a total market of around 10 million charging points.

With the target market derived above, it is possible to show the next technical and business steps.

1.5 Go-To-Market Strategy and Roadmap

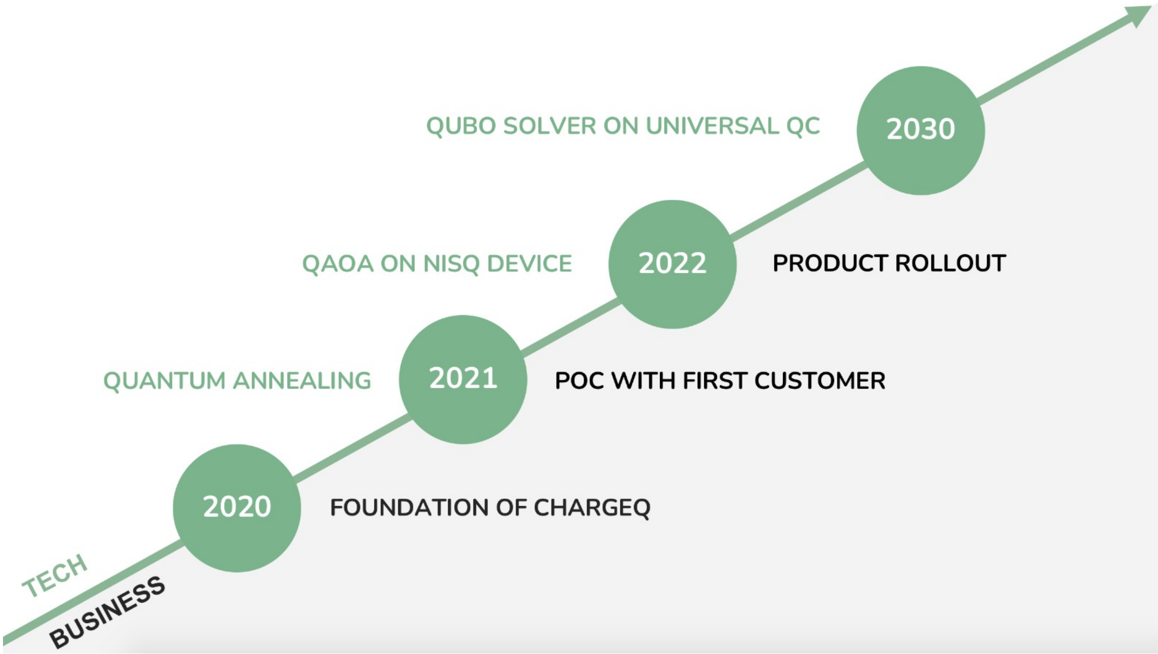


Figure 1.2: Roadmap (own illustration)

In our Big Picture, we combine several optimization problems into a networked service. In the following, the differentiated steps are briefly explained, divided into three evolutionary stages - short-term, mid-term and long-term.

Within the target picture for the short-term solution respectively the first use case, the scheduling problem at charging stations is solved in the urban area of the metropolis Munich. In the second stage, the area will be extended to the entire German market. Within the third stage the additional optimization use case will be launched in parallel for the pilot market Munich. In this supplementary case we aim to optimize the electricity price for the charging station provider. ChargeQ strives to optimize the purchase of electricity units, together

[6] https://www.muenchen.de/verkehr/aktuell/2020/swm-e-ladesaeulen.html

[7] https://www.capgemini.com/de-de/wp-content/uploads/sites/5/2019/08/Wachstumsmarkt-Ladeinfrastruktur-in-Deutschland-Capgemini-Invent.pdf

with the respective DSO, so that they are sourced optimally and, above all, at the most favorable conditions. In this way, we combine scheduling with the optimal amount of electricity to be purchased and optimize the entire case.

The big picture, i.e., the long-term goal, then envisages this overall solution for the entire German market. We then act as a provider of a complete solution for the purchase and distribution of electricity capacity for EVs. In this holistic offer we can provide benefits for our main customers the DSO and the EV owner - and in the second use case also for the charging station provider.

As shown in the illustration (Figure 1.2), the goal of Charge Q is to take the first productive steps with a lighthouse customer in 2021. The focus is on a joint proof of concept (POC), which contains the values and USPs tailored to the customer. If the pilot phase is successful, the product roll-out will take place in 2022. Building on this, the aim is to approach the SOM calculated for 2030.

1.6 Competitor Analysis

We analyzed our competitive landscape and found the following players in the field. All competitors are also new in the field with a founding date between 2016-2018. Only Virta, which focuses on developing charging stations, is more established with funding in 2013 and a successful series A financing round. Among all these companies, ChargeQ is the only one that applies quantum algorithms - this is what sets us apart.

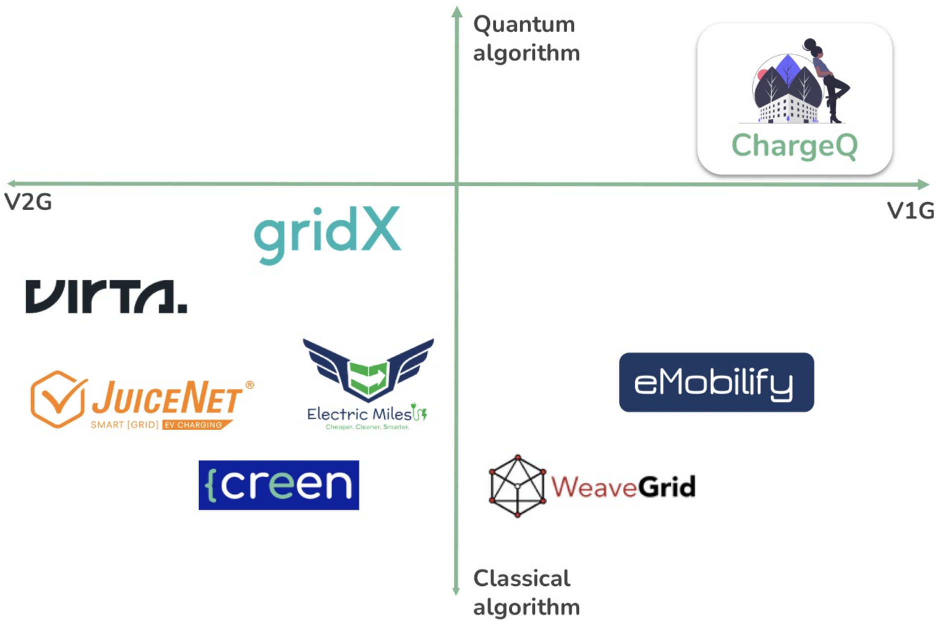


Figure 1.3: Competition (own illustration)

1.7 Key Partners

We aim to partner with dominant charging stations providers to leverage their data for our optimizations. There are different kinds of companies that have a share of this market. First, the majority of EV manufacturers such as VW and Tesla are also offering their own charging infrastructure. Furthermore, most of the energy suppliers such as EnBW and Stadtwerke München maintain their own charging stations. Lastly, innovative startups have entered the market such as Fastned, Ionity and Wirelane. We are already in discussions with a majority of these companies and are looking forward to partnering with them. Besides the economic partnering ChargeQ is also planning to use strategic partnerships in the field of QC and Quantum Annealing to improve the technical assets and algorithms.

1.8 Pricing

1.8.1 Revenue streams

In the case of the pricing model, ChargeQ is based on a combination of a flat rate for using the API and algorithms and a usage-based share, which is calculated on the basis of the additional costs avoided as a result of electricity peaks. Thus, the DSO is also on the safe side and pays only a part of its otherwise incurred costs for a now stable network. Since the focus is currently only on one customer group and only one use case is being offered in the pilot phase. Pricing here was based on the transformation costs of the DSOs. As described in detail in the Oliver Wyman study, these costs for adapting the power grid to the increasing number of EVs amount to 11 billion euros by 2032 .[8] Conservatively calculated, this means an annual burden of at least 785 million euros per year in transformation costs alone. Per month, that's just under €65 million, which translates to more than €325 per charging point, assuming 200,000 charging points in 2020. ChargeQ's combined price model would charge on average a monthly rate of €10 per month per charging point, which is only three percent of these costs for the DSOs. The pricing strategy here is the penetration strategy, as important market shares are to be captured in the beginning. Then, once the second optimization use case is started, it changes to the tiered pricing model. Here, one can then decide between the two use cases or obtain the complete solution. To stay competitive in such a volatile environment the revenue stream adapts to a changing business model. For the first use case ChargeQ tackles the transitional period where the DSOs won't be able to stabilize the electricity grid because of the rising demand. Besides helping with the transition the overarching goal is to gain market share that is needed for the second use case where the grid is stabilized and the business model changes to a V2G provider.

1.8.2 Cost structure

The cost side is currently still being elaborated together with the target customers, therefore the focus in the following is laid on the cost structure without going into detail of the exact figures. The blocks are divided as follows: development personnel, development cost, maintenance personnel and the cloud service running cost.

The first block of development costs personnel includes personnel costs for software engineers, user interaction designer as well as marketing respective CRM and finance. The second block relates to developer software, equipment and licenses, as well as marketing and advertising. The third block of costs, maintenance personnel, includes site reliability engineers (on-calls), hot-line and customer support, and (at least) one data protection officer. In the last part the cloud service running costs are considered, a distinction is made between the overall hosting and domain costs and the externally sourced quantum services.

[8] Friedl, G & et al.: BLACKOUT - E-Mobility puts pressure on grid operators *Oliver Wyman*, 2018

Chapter 2

Technology

In order to solve the load balancing problem for electric vehicles (EVs) and grids, the optimal charging order for electric vehicles connected to the grid must be determined. First, we demonstrate that the problem can be represented as the job shop problem, which was proven to be NP hard by Garey in 1976.[1] Then, we show that for combinatorial optimization a mapping to the quantum annealing algorithm is possible leading to a possibly exponential advantage and conclude that in a few years a quantum advantage can be reached. Finally, we offer a tour through our prototype.

2.1 Classical Algorithms

At the heart of our product is a scheduling problem. This broad class of problems deals with the allocation of limited resources and has applications in diverse application domains as manufacturing and computing itself.[2] For this reason, scheduling problems are some of the most intensively studied problems in computer science.

Machine (or processor) scheduling problems are generally classified based on three criteria concerning the available machines , additional restrictions and the optimization goal .[3] A specific scheduling problem is then described by a triple of symbols in square brackets: $[\ |\ |\ ]$. Options for the first criterion are e.g. "1" if there is a single machine, "IP" if there are several identical machines for parallel task processing and "UP" if there are several machines that are not identical, i.e. with different processing speeds. The last criterion refers to the optimization goal which is denoted as e.g. "Z" if it is to minimize the total time required to finish all tasks, "T_{max}" if it is to minimize the maximum tardiness or "U" if it is to minimize the total number of tardy tasks. The additional restriction on the processing of the tasks include such options as "pmnt" if the processing of tasks can be interrupted and resumed at a later time without having to start over, or "r_j" if for each task j there is specific earliest possible start time "r_j". Each of these slightly different problems can in principle be of a different complexity and require a different algorithmic approach to solve it. In this problem space, there are plenty of NP-hard problems for some of which exist good heuristics. In many cases, the addition or omission of a single additional property in can make an NP-hard problem easy to solve and conversely make a fairly simple problem NP-hard.

Scheduling Problem	NP-Hardness	Approximation	Complexity	Heuristics
$[1\|\|\sum U_J]$	No	EDD-Algorithm	$O(n \log n)$	
$[1\|\|\sum w_J U_J]$	Yes (weakly)	Sahni 1976	$O(n \sum w_J)$	
$[1\|prec\|\sum U_J]$	Yes (strongly)	Ibarra and Kim 1978	$O(kn(k+2))$	
$[P\|\|\sum w_J U_J]$	Probably yes			
$[P\|prec\|\sum U_J]$	Yes (strongly)	-	-	Johnson's rule

Table 2.1: Run time of classical algorithms. Source: Blazewicz, J.; Ecker, K. H.; Pesch, E.; Schmidt, G. & Sterna, M. Handbook on Scheduling *Springer-Verlag GmbH*, 2019

Our most realistic vehicle charging problem corresponds to a job shop, a well-studied subclass of scheduling problems as it models realistic manufacturing processes. It is well known that for most practical scenarios, the job shop problem is NP-hard. In 1972, Garey proved that the problem is NP-complete if there are three or

[1] Garey, M. R.; Johnson, D. S. & Sethi, R.: The Complexity of Flowshop and Jobshop Scheduling *Mathematics of Operations Research, Institute for Operations Research and the Management Sciences (INFORMS)*, 1976, 1, 117-129

[2] Graham, R. L.: Bounds for Certain Multiprocessing Anomalies *Bell System Technical Journal, Institute of Electrical and Electronics Engineers (IEEE)*, 1966, 45, 1563-1581

[3] MacCarthy, B. L. & Jiyin, Liu: Addressing the gap in scheduling research: a review of optimization and heuristic methods in production scheduling *International Journal of Production Research, Informa UK Limited*, 1993, 31, 59-79

more machines. There exist some heuristics, including Johnson's rule, local search and genetic algorithms. The classical heuristics for good job shop schedules can serve as a starting point, even in the absence of quantum processors with a sufficiently large number of fault-tolerant qubits. However, with potentially hundreds of thousands of EVs to be charged on the same urban electricity grid, these heuristics will most likely not lead to satisfactory results in a reasonable amount of time.

2.2 Quantum Algorithms

In this section, we provide a brief summary of the quantum algorithm implementation and mapping of our problem. In 2016, Venturelli et al. published a quantum annealing based algorithm for a job shop scheduling solver.[4] As previously introduced, the job shop scheduling problem is the hardest case of our proposed vehicle charging problems. Here, the optimization goal was the minimal makespan. As we want to optimize the weighted number of tardy tasks, our approach leads to a different cost function, but can profit greatly from the general structure of the problem's formulation.

The approach can be summarized as follows: First the makespan-minimization problem is reformulated as a series of decision instances, which are then casted into a time indexed quadratic unconstrained binary optimization (QUBO). In order to deliver the QUBO to D-Waves quantum annealer Venturelli et al. propose different pre-processing steps that lead to an optimal performance on next generations quantum annealers.

The job shop problem consists of $J = \{j_1, \dots, j_N\}$ jobs and $M = \{m_1, \dots, m_M\}$ machines. Each job contains a series of L_n operations $j_n = \{O_{n1} \rightarrow \dots \rightarrow O_{nL_n}\}$ which needs to be executed by a machine m. How can we translate this problem into a quantum problem?

2.2.1 Quantum annealing requirements

In order to make use of the quantum annealer's capabilities, we need a problem translation to the form of an Ising spin glass model or better known as QUBO. Here, we construct a graph where each node and edge is physically represented as a qubit. After each linear or quadratic value is attached to a qubit, the annealer is expected to find a global minimum depending on the device's parameters.

2.2.2 QUBO Formulation

Charging boundaries

Firstly, we introduce n cars $[x_0, x_1, \dots, x_n]$, where each car has a charge demand, which is defined as a number of charging portions of an arbitrary unit: $[c_0, c_1, \dots, c_n]$. We define the array of cars to be a boolean array, where a value of 1 in the index i denotes that the i-th car is charged, and a value of 0 denotes that it is not charged. We also have a maximum available charge M, given in the same units.

This problem is reducible to the knapsack problem. Therefore, there exist two constraints that need to be implemented in this step:

- The sum of charging cars should be lower than or equal to the maximum capacity M.
- The optimal solution occurs when the sum of charging cars is as near as possible to M.

The first item can be implemented by introducing a second, "artificial" variable $y_i \in [y_0, y_1, \dots, y_m]$ is a boolean array for $m \leq M$). This variable represents the sum of the charging portions of the currently charging cars and it is needed to ensure that the total sum stays under the maximum value M. The sum is modeled by a multiplication of a boolean y_i, being either true (1) or false (0), with its index, i, therefore when the n-th variable is set, it means that the total sum is $y_n \cdot n = 1 \cdot n = n$. The formula should reach 0 whenever the total sum of charges is below M, because an appropriate $y_i \cdot i$ can be found/constructed such that the difference between the two cancels out to (the optimal value of) 0; and it reaches values > 0 if the sum is greater than M.

$$\left(\sum_{i=0}^{M} i y_i - \sum_{j=0}^{n} c_j x_j \right)^2 \tag{2.1}$$

Because of the design choice that this variable is part of a boolean array, where exactly one of the elements is true, and the others false, we introduce another factor that ensures that exactly one y_i is set to true (1), and the rest is false (0). This models the fact that the sum of all currently charging portions can only have one value at a time.

$$\left(1 - \sum_{i=0} y_i \right)^2 \tag{2.2}$$

[4] Venturelli, D.; Marchand, D. J. J. & Rojo, G.: Quantum Annealing Implementation of Job-Shop Scheduling 2015

Combined, these yield the first constraint of the QUBO formulation, prepended with a weight factor P_0 to balance the constraints out. The formula ensures that the total sum stays under M, but tries to get as close as possible to M:

$$H_0 = P_0 \left[\left(1 - \sum_{i=0} y_i \right)^2 + \left(\sum_{i=0}^{M} i y_i - \sum_{j=0} c_j x_j \right)^2 \right] \tag{2.3}$$

Benefit/Prioritization

To introduce a prioritization scheme for choosing one car over another, a variable $p_i \in \{p_0, p_1, \ldots, p_n\}$ is introduced for each car. The values of these represent the result of a combination of different prioritization or benefit factors. For example, emergency vehicles such as ambulances and fire trucks can be prioritized over other vehicles.

The value should contribute to the formulation if the car is charging, otherwise it should be 0:

$$H_1 = P_1 \sum_{i=0} p_i x_i \tag{2.4}$$

Charge completion Penalty and Deadlines

In this step, we introduce the concept of charging times. We define a time frame unit of arbitrary choice, for example a 15 minute time frame, as t_i. Each car has a charge completion demand of a number of these time frames, $ct_i \in \{ct_0, ct_1, \ldots, ct_n\}$. Additionally, every car has a deadline $d_i \in \{d_0, d_1, \ldots, d_n\}$, where the number d_i denotes the amount of time frames after which the i-th car should be charged. In our example, this could model the fact that the car user wants to depart after $d_i \cdot 15$ minutes.

We want to model a penalty for assigning a car in a time frame if the car already got more charging time frames as it needed. This ensures that cars that have fully charged are not assigned another charging time frame. In addition, the assigned time frames should happen before the d_i-th time frame, to take into account the car's deadline:

$$H_2 = P_2 \sum_{i=0} \left(t_i - \sum_{t=0}^{d_i} x_{it} \right) \tag{2.5}$$

The three constraints together yield this QUBO formulation:

$$H = P_0 \left[\left(1 - \sum_{i=0} y_i \right)^2 + \left(\sum_{i=0}^{M} i y_i - \sum_{j=0} c_j x_j \right)^2 \right] - P_1 \sum_{i=0} p_i x_i + P_2 \sum_{i=0} \left(t_i - \sum_{t=0}^{d_i} x_{it} \right) \tag{2.6}$$

2.2.3 Output translation

Of course, we are interested in the output of the quantum annealer. Here, the solution is straightforward: As we defined our binary variables as $x_i; t = \{1; 0\}$ for operation i at time t, we can translate the minimum solution directly to a Gantt chart.

2.2.4 Runtime and limitations

In general an ab initio guess for the run time is not possible and would require the knowledge of the scaling of noise, number of qubits, and annealing cycles.[5] However, the approximation by Venturelli gives first hints: There, each cycle lasted $t = 20 \cdot 10^{-6}s$. For a 99% probability of success, the algorithm was still outperformed by classical machines, as the studied problem size was limited to the capability of the D-Wave device. Still, the complexity of the quantum problem scales with the number of qubits leading to an at least polynomial run time, whereas the best classical algorithms already fail at 20 × 20 job shop problems due to the exponential scaling of the solution space. In particular, Applegate and Cook analyzed the difference between a still solvable MT10 problem, a specific 10 × 10 problem, which was already theoretically solvable by large supercomputers in 1.5 h by 1991, and larger problems. They found that any problem larger than 15 × 15 poses extreme challenges to classical computers and is practically unsolvable in a reasonable human timescale. In fact, a linear increment on the problem space leads to a factor of 1000 in required computation nodes.[6]

[5] Venturelli, D.; Marchand, D. J. J. & Rojo, G.: Quantum Annealing Implementation of Job-Shop Scheduling 2015

[6] Applegate, D. & Cook, W.: A Computational Study of the Job-Shop Scheduling Problem *ORSA Journal on Computing, Institute for Operations Research and the Management Sciences (INFORMS)*, 1991, 3, 149-156

2.2.5 Benchmarking

We are looking forward to benchmark our own classical and quantum algorithms, by using publicly available global solutions to the job shop problem by Taillard.[7] With the help of this data set, we can obtain valuable insights into the quality of our algorithms up to a size of 15 15 for particular problem formulations. To validate bigger problem spaces we hope to adopt the usage of lumped, separable or approximate problem formulations that can both still be validated on classical computers but also extend to a problem size were we hope to surpass classical computers. We were inspired by the elided circuit method used by Arute et al. in the famous Quantum supremacy paper.[8] For example, one could to evaluate the convergence of each part of the Hamiltonian separately and compare it with the convergence rate of the full Hamiltonian. Another topic of interest is the effect the simultaneous computation of separable problems depending on the physical implementation of the circuit.

2.3 System Architecture and User Journey

Our end-to-end solution has two users:

- *The EV user:* Any person owning an EV that wants to charge their car. They are interested in the guarantee to have a car that is charged sufficiently for their travels.
- *The electricity grid manager:* The organisation that handles and maintains the charging stations for EVs in a city. They want to enable their grid users with enough capacity, and worry that EVs that are using the charging stations above their limits cause the grid to collapse. They want to see where this is likely to happen and they wish for a tool that is low-effort and handles the charging station optimization for them.

Our solution is targeted towards both users, in a way that each of them gets a package that is valuable to them (see Fig. 2.1):

- The user uses our MyCharge-App to modify and administrate their user information so that they can play their part in maintaining a working grid.
- The ChargeQ service runs in the cloud. It collects the user data from the MyCharge app and combines it with the information from the charging stations. These inputs are then used in our algorithm to calculate the optimal scheduling for the charging jobs.
- The grid manager uses our MyGrid monitoring software that shows them an overview of the grid's performance, including analytics and hotmaps of the charging stations for EVs. The program also enforces the schedules on the charging stations.

2.3.1 Implementation details

The user-sided app is built in Flutter, a UI Framework that is capable of compiling not only into Android and iOS systems, but also Web Apps and Windows, macOS and Linus distributions. This makes the user sided app a multi-platform tool that can be used by any user, with any platform, maximizing the user reach. The software features an easy to understand UI to enter trips manually, including repetitions if necessary, and, due to the easy integration into Firebase ML libraries, it is designed to also predict user patterns and/or extract trip information from other apps like the calendar or maps service (which the user has to approve). This makes the need and effort for user interaction minimal, while ensuring a good approximate of the user's needs. At the same time, the user wins when entering more accurate data manually because this ensures that the scheduling service can honor the needs more precisely.

The ChargeQ scheduling service runs in a cloud service, and interacts with a cloud-run Quantum Computing service of choice through common APIs for the scheduling algorithms. Lastly, the MyGrid Software is recommended to be written in Flutter as well, to enable web- and operating system compatibilities and potentially even code-sharing between the MyCharge and the MyGrid code.

---

[7] Taillard, E.: Benchmarks for basic scheduling problems *European Journal of Operational Research, Elsevier BV, 1993, 64, 278-285*

[8] Arute, F. et al.: Quantum supremacy using a programmable superconducting processor *Nature, Springer Science and Business Media LLC*, 2019, 574, 505-510