Womanium Quantum Hackathon 2022
Green Qupermarket (Deloitte)

Problem Statement

Team Qrious

August 23, 2022

1 Introduction

The goal of the Green Qupermarket challenge is to analyze how quantum technology can optimize the energy consumption model of supermarkets in regard to its CO2 emissions.

2 Input Data

We have a set of input data featuring solar plant production charts for all week days related to the weather and a set of vehicle data providing arrival and departure hours and minimum admitted battery charge at departure. In figures 1 solar energy production and energy need is displayed with respect to the time of the day and the day of the week. The contribution in kW produced or utilized in a half an hour time bin is displayed in the graph. Figure 2 features a histogram of arrival times for vehicles during daytime over the weekdays.
Figure 3 features a histogram of contemporaneous presence of vehicles in the mall parking during daytime over the weekdays.

3 Preliminary review of CO2 emission

Based on only solar plant production and energy need, we can evaluate the CO2 emission plot over week for the worst case scenario, considering a solution with no batteries in the mall and no car contributions. In equation we can consider a plot of the Co2 emission for each time frame of the week dataset, denoting as C_{CO2} the quantity in grams of carbon dioxide produced in half an hour on exclusive plug energy contribution.

$$C_{CO2} = c_{plug}E_{plug} = c_{plug}\max(E_{need} - E_{solar}, 0) \tag{1}$$

In figure 4 we show the trend of emissions during the week

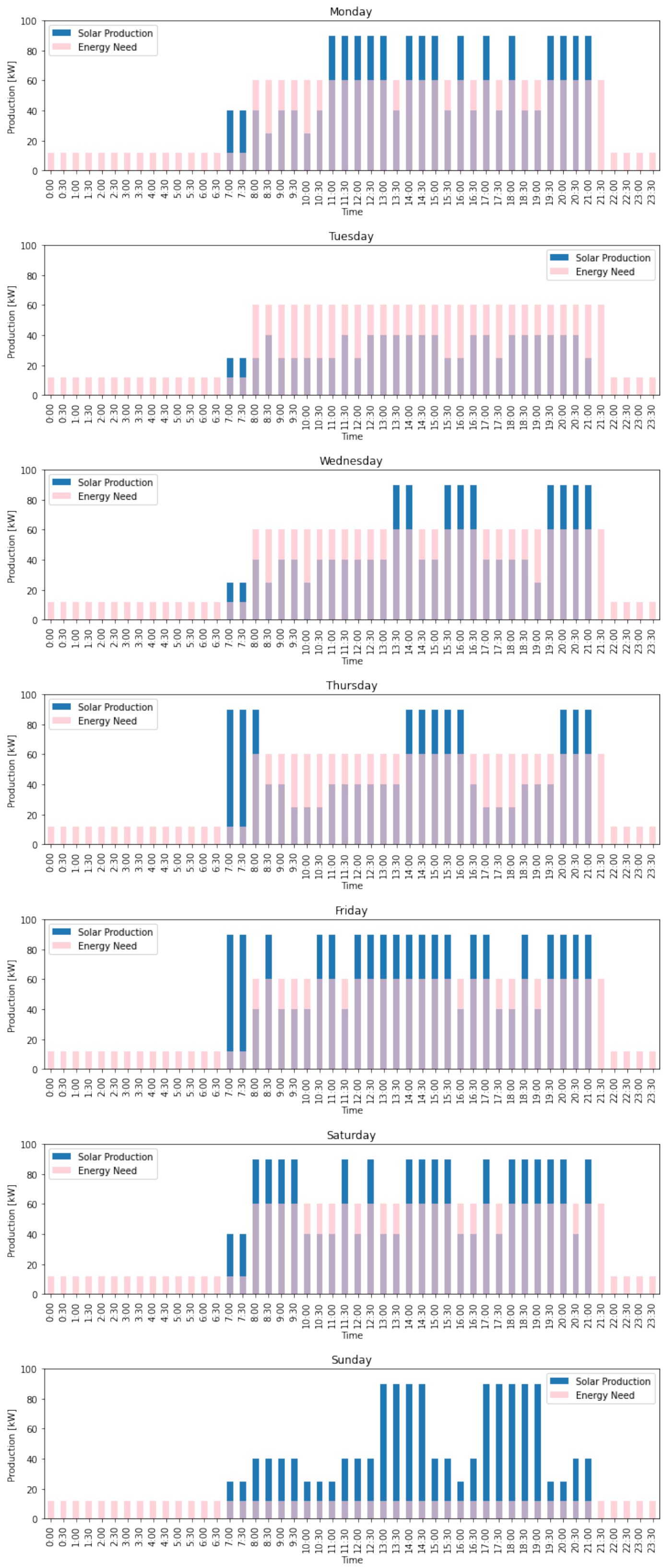

Figure 1: Solar energy production and energy need during daytime over the week days.

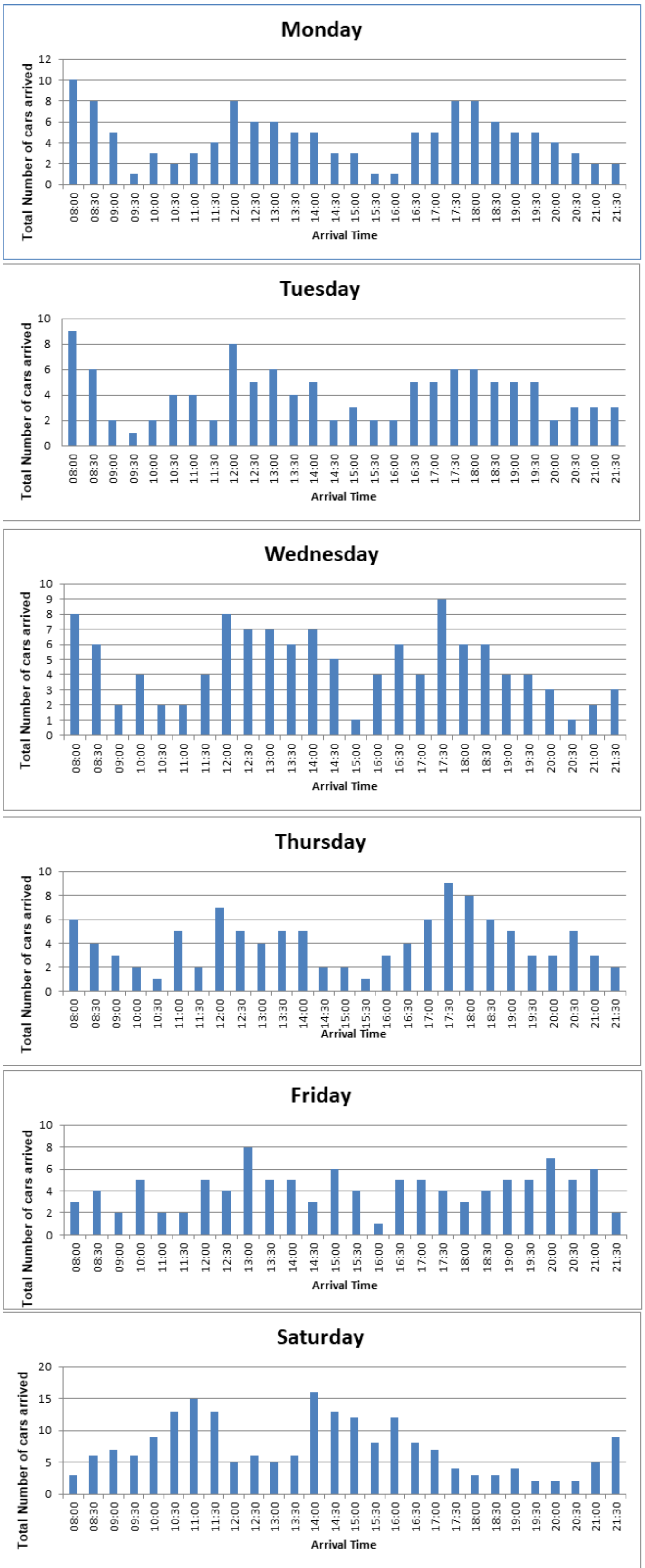

Figure 2: Arrival time histogram for vehicles during week days.

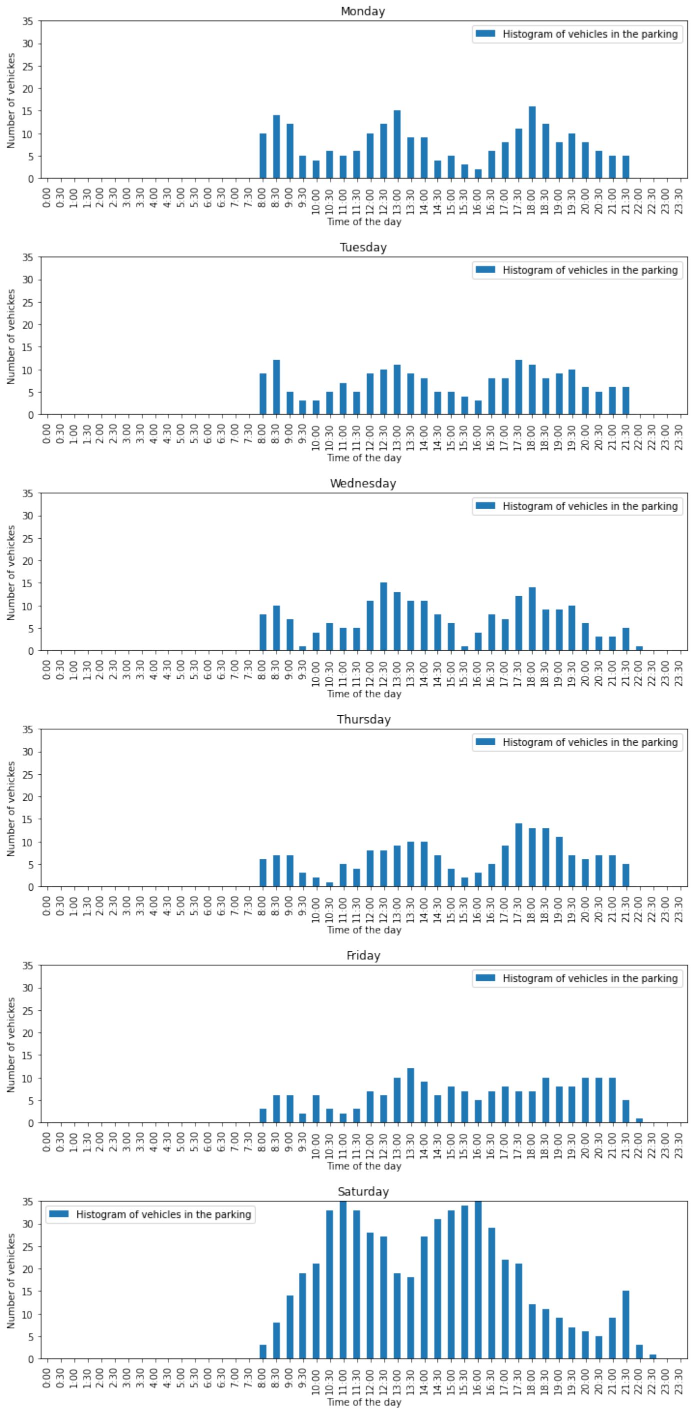

Figure 3: Presence histogram in the parking for vehicles during week days.

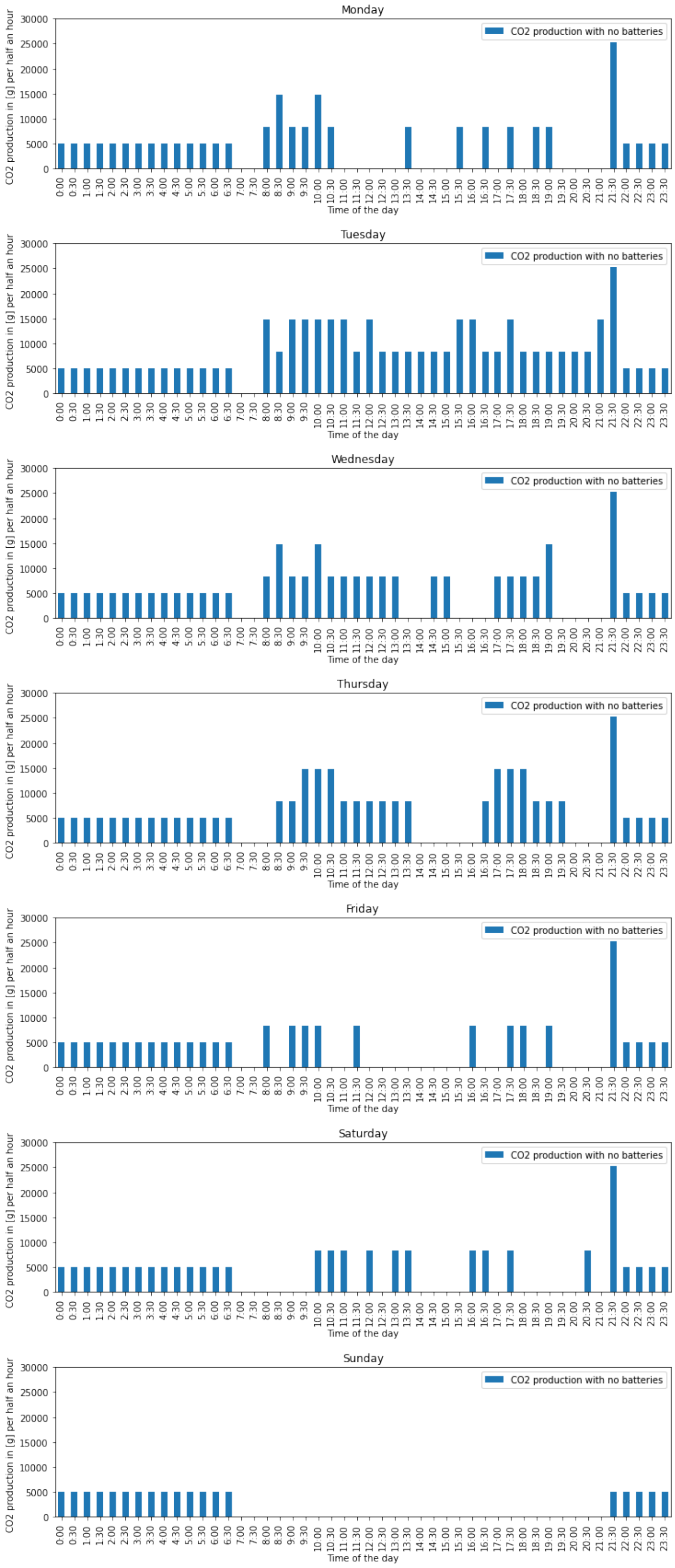

Figure 4: CO2 emissions over the week for the worst case scenario

4 Mathematical description

For the sake of simplicity, we consider as maximum value of the time frame the half-an-hour interval proposed in the input data, and we state that the optimization procedure must be run at each time frame to balance the current contributions. In the cost function below, Electric Vehicle Discharging (EVD), Electric Vehicle Recharging (EVR), Solar Plant System (SPS) and Plug contributions are taken into account to shape the quantity that must be minimized at each time frame:

$$C_{CO2} = \sum \big(C_{plug} + C_{EVD} + C_{EVR} + C_{SPS} \big) \tag{2}$$

where

$$\begin{aligned} C_{plug} &= c_{plug} E_{plug} && (3) \\ C_{EVD} &= c_{disc} \sum_{i=1}^{N_{disc}} \tau_i^{(disc)} && (4) \\ C_{EVR} &= c_{charge} \sum_{i=1}^{N_{char}} \tau_i^{(charge)} && (5) \\ C_{SPS} &= c_{solar} E_{solar} && (6) \end{aligned}$$

.
Other constraints must be set to privilege vehicles that must meet the right minimal charge value at departure, and to do this we have to keep track of the departure times.
The coefficients that CO2 emission cost per KWh are $c_{plug} = 420$, $c_{disc} = 84$, $c_{charge} = -84$, $c_{solar} = 0$.
Remark that the last term of eq. 2 vanishes; we have to keep into account the imbalance between solar energy production, mall battery recharging process and mall battery discharge process in the energy term E_{plug}.
Denoting with BD and BR the Battery Discharge and Recharge process of the mall storage of electricity (their capacity is 500 kWh) and labeling as E_{req} the energy per hour (120 kWh per hour in the opening hours and 24 kWh per hour in the rest hours), we can write the expression for the energy

$$E_{plug} = E_{BRT} - E_{BDT} - (E_{solar} - E_{need}) \tag{7}$$

As far as the mall battery charging and discharging model, denoting with r_{BR} the battery charging rate, and as r_{BD} the battery discharging rate, we can consider two situations:

1. a lumped battery model where, where τ_{BD} and τ_{BR} are binary variables that switch the mall battery discharge and recharge process. These two variables are not independent and their value is an output of the optimisation run. The first constraint that we can imagine is that the battery either charges or discharges or do nothing. Let's denote as BC the energy level of the battery, that is a value that change over time and ranges from 0 to the capacity of the battery in kW. This can be stated as

$$\begin{aligned} &E_{BRT} = r_{BR} \Delta t \, \tau_{BR} && (8) \\ &E_{BDT} = r_{BD} \Delta t \tau_{BD} && (9) \\ &\tau_{BR} + \tau_{BD} \leq 1 && (10) \\ &\tau_{BR} = 0 \ \text{ if } \ BC(t) = 500 && (11) \\ &\tau_{BD} = 0 \ \text{ if } \ BC(t) = 0 && (12) \end{aligned}$$

and a linear law to update the charge value, once the solution of the optimization process has determined the value of the binary variables τ_{BD} and τ_{BR}

$$BC(t+\Delta t) = BC(t) + r_{BR}\Delta t \tau_{BR} - r_{BD}\Delta t \tau_{BD} \tag{13}$$

2. a distributed model of ten batteries where, for $j = 1..10$, $\tau_{BD}^{(j)}$ and $\tau_{BR}^{(j)}$ are binary variables that switch the mall battery discharge and recharge process. For each battery j each couple of associated binary variables is not independent and their value is an output of the optimisation run. The first constraint that we can imagine is that the battery either charges or discharges or do nothing. Let's denote as $BC^{(j)}$ the energy level of the battery, that is a value that change over time and ranges from 0 to the capacity of the battery in kW. This can be stated as

$$E_{BRT} = \sum_{j=1}^{10} r_{BR}\Delta t\, \tau_{BR}^{(j)} \tag{14}$$

$$E_{BDT} = \sum_{j=1}^{10} r_{BD}\Delta t \tau_{BD}^{(j)} \tag{15}$$

$$\tau_{BR}^{(j)} + \tau_{BD}^{(j)} \leq 1 \qquad \text{j= 1 ..10} \tag{16}$$

$$\tau_{BR}^{(j)} = 0 \ \text{ if } \ BC^{(j)}(t) = 50 \qquad \text{j= 1 ..10} \tag{17}$$

$$\tau_{BD}^{(j)} = 0 \ \text{ if } \ BC^{(j)}(t) = 0 \qquad \text{j= 1 ..10}$$

(19)

and a linear law to update the charge value, once the solution of the optimization process has determined the value of the binary variables τ_{BD} and τ_{BR}

$$BC^{(j)}(t+\Delta t) = BC^{(j)}(t) + r_{BR}\Delta t \tau_{BR}^{(j)} - r_{BD}\Delta t \tau_{BD}^{(j)} \ \ j = 1..10 \tag{20}$$

In equation 7 E_{need} stands the energy needed per hour day for the daily operations such as lighting, freezing and frozen storage and cashier system, and takes the values 120 kWh per hour in the opening hours (8.00 am to 10.00 pm, Monday to Saturday) and 24 kWh per hour in the rest hours.
In the electric vehicle discharge and recharge terms we have considered two sets of binary variables: $\tau_i^{(disc)}$ that switch on and off the discharging process of each vehicle and $\tau_i^{(charge)}$ that act on the discharging process of each vehicle that is present at the given time frame. These two sets of variables are dependent and their value is an output of the optimisation run. For the electric vehicle discharge and recharge process we can depict three situations

1. we only choose to either charge vehicles or do nothing and we do not discharge them: $\tau_i^{(disc)} = 0$ and $\tau_i^{(charge)} = \{0,1\}$;

2. we either charge vehicles or discharge them, doing nothing is not allowed: $\tau_i^{(disc)} = 1 - \tau_i^{(charge)}$ and $\tau_i^{(charge)} = \{0,1\}$;

3. three are the valid states for car batteries: charge, discharge and do nothing $\tau_i^{(charge)} = \{0,1\}$, $\tau_i^{(disc)} = \{0,1\}$ and the constraints between them are $\tau_i^{(disc)} + \tau_i^{(charge)} \geq 0$ and $\tau_i^{(disc)} + \tau_i^{(charge)} \leq 1$.

we have to set also binary values constraints
In each case we have to consider for the N_v vehicles simultaneously present at the given time frame the charge percentage at arrival p_i^a and the charge percentage at departure p_i^d, so we have additional constraints

$$\tau_i^{(charge)} = 0 \text{ if } BC_i^{(v)}(t) = 50 \qquad \text{i= } 1\,..\,N_v \quad (21)$$

$$\tau_i^{(disc)} = 0 \text{ if } BC_i^{(v)}(t) = 0 \qquad \text{i= } 1\,..\,N_v \quad (22)$$

and a law for the battery capacity BC_i^v for the vehicles.Indicating with C_{max}^v the capacity of the battery

$$BC_i^v(t+\Delta t) = BC_i^v(t) + r_v \Delta t \tau_i^{(disc)} - r_v \Delta t \tau_i^{(charge)} \quad i = 1\,..\,N_v \qquad (23)$$

$$BC_i^v(t_a) = p_i^a BC_{max}^v \qquad (24)$$

As we are doing a coarse grain modeling on the time line, setting the time interval to half an hour, for the moment we drop the linear law for the batteries and we set priority with different policies . Gathering all terms, our CO2 emission function for each half an hour time slot reads as:

$$C_{CO2}(t) = c_{plug}\max\Big(E_{BRT} - E_{BDT} - E_{solar} + E_{need}, 0\Big) + c_{disc}\sum_{i=1}^{N_{disc}} \tau_i^{(disc)} + c_{charge}\sum_{i=1}^{N_{char}} \tau_i^{(charge)} \qquad (25)$$

5 Candidate optimization functions

To minimize it in a feasible way for a quantum device the minimization problem can be stated in different ways. Denoting as $E_{imb} = E_{solar} - E_{need}$

5.1 Instantaneous optimization

5.1.1 Motivation

The instantaneous optimization function is designed to balance the energy contributions at each time frame, considering only vehicles that are contemporaneously present in the parking. The tracking of the battery level of the cars is performed via state variables that are updated at each time frame

5.1.2 Mathematical statement

As quantum annealers are sensitive to linear and quadratic terms but totally deaf to the offset, we square the CO2 production function in equation 25 in order get the minimal energy configuration when $f(t)$ approaches to zero and we write the instantaneous cost function that has to be minimized at each time frame. In the following we denote as E_{BR}, E_{BD}, E_{imb} the corresponding energy contributions in the time interval Δt of half an hour.

$$\left(a_{plug}\big(E_{BR}\tau_{BR} - E_{BD}\tau_{BD} - E_{imb}\big) + a_{disc}\sum_{i=1}^{N_v} r_v \Delta t \tau_i^{(disc)} + a_{charge} r_v \Delta t \sum_{i=1}^{N_v} \tau_i^{(charge)}\right)^2$$

where a_{plug}, a_{disc} and a_{charge} are suitable float constants associated to priorities in charging and discharging. In calculations a_{plug} will have the lowest value as we want to minimize the plug energy that provides the highest contribution for CO2 production.

Squaring the terms and reordering we will get

$$
\begin{aligned}
&a_{plug}^2\big(E_{BR}^2\tau_{BR}^2 + E_{BD}^2\tau_{BD}^2 + E_{imb}^2\big) + a_{disc}^2\sum_{i=1}^{N_v} r_v^2\Delta t^2\tau_i^{(disc)2} + a_{charge}^2 r_v^2\Delta t^2\sum_{i=1}^{N_v}\tau_i^{(charge)2} + \\
&+a_{plug}^2\Big(-2E_{BR}E_{BD}\tau_{BR}\tau_{BD} - 2E_{imb}E_{BR}\tau_{BR} + 2E_{imb}E_{BD}\tau_{BD}\Big) - \\
&-2a_{plug}a_{disc}E_{BR}r_v\Delta t\sum_{i=1}^{N_v}\tau_i^{(disc)}\tau_{BR} - 2a_{plug}a_{disc}E_{BD}r_v\Delta t\sum_{i=1}^{N_v}\tau_i^{(disc)}\tau_{BD} + \\
&+2a_{plug}a_{charge}E_{BR}r_v\Delta t\sum_{i=1}^{N_v}\tau_i^{(charge)}\tau_{BR} + 2a_{plug}a_{charge}E_{BD}r_v\Delta t\sum_{i=1}^{N_v}\tau_i^{(charge)}\tau_{BD} + \\
&-2a_{plug}a_{disc}E_{imb}r_v\Delta t\sum_{i=1}^{N_v}\tau_i^{(disc)} + 2a_{plug}a_{charge}E_{imb}r_v\Delta t\sum_{i=1}^{N_v}\tau_i^{(charge)} + \\
&+2a_{disc}a_{charge}r_v^2\Delta t^2\sum_{i=1}^{N_v}\sum_{k=1}^{N_v}\tau_i^{(disc)}\tau_k^{(charge)} \qquad (26)
\end{aligned}
$$

As the quantum annealer behaves like a fixed precision hardware and has limited embedding capacity of a complete graph, we choose to neglect quadratic terms like

$$2a_{disc}a_{charge}r_v^2\Delta t^2\sum_{i=1}^{N_v}\sum_{k=1}^{N_v}\tau_i^{(disc)}\tau_k^{(charge)} \qquad (27)$$

as the related quadratic terms correspond to a dense matrix block that cannot be efficiently represented by the embedding procedure.
Reordering quadratic and linear terms and keeping in mind that the square of a binary variable is the binary variable itself, we obtain the cost function

$$
\begin{aligned}
f(t) = \quad & -2a_{plug}^2E_{BR}E_{BD}\tau_{BR}\tau_{BD} - \\
&-2a_{plug}a_{disc}E_{BR}r_v\Delta t\sum_{i=1}^{N_v}\tau_i^{(disc)}\tau_{BR} - 2a_{plug}a_{disc}E_{BD}r_v\Delta t\sum_{i=1}^{N_v}\tau_i^{(disc)}\tau_{BD} + \\
&+2a_{plug}a_{charge}E_{BR}r_v\Delta t\sum_{i=1}^{N_v}\tau_i^{(charge)}\tau_{BR} + 2a_{plug}a_{charge}E_{BD}r_v\Delta t\sum_{i=1}^{N_v}\tau_i^{(charge)}\tau_{BD} + \\
&+(a_{plug}^2E_{BR}^2 - 2a_{plug}^2E_{imb}E_{BR})\tau_{BR} + (a_{plug}^2E_{BD}^2 + 2a_{plug}^2E_{imb}E_{BD})\tau_{BD} + \\
&+(a_{charge}^2r_v^2\Delta t^2 + 2a_{plug}a_{charge}E_{imb}r_v\Delta t)\sum_{i=1}^{N_v}\tau_i^{(charge)} \\
&+(a_{disc}^2r_v^2\Delta t^2 - 2a_{plug}a_{disc}E_{imb}r_v\Delta t)\sum_{i=1}^{N_v}\tau_i^{(disc)} + a_{plug}^2E_{imb}^2 \qquad (28)
\end{aligned}
$$

where the last term is the offset and will normally have little effect on the quantum annealer. To cope with the three-state battery layout for both mall and vehicle batteries, in addiction to charging and discharging qubits we introduce another slack binary variable τ_{add} that allows to define a corresponding constraint with linear and quadratic penalty terms. The above cost function is also constrained by the following equations

$$\tau_{BR} + \tau_{BD} + \tau_{add} = 1 \quad (29)$$
$$+\text{constraints arising from the vehicles}$$

In the present implementation we drop the expression like $a^2_{charge} r^2_v \Delta t^2$ from the linear terms in equation 28 preserving the dominant effect of E_{imb} in changing the signs of the linear terms during the optimizations. Moreover we plan to act on individual coefficients a_{charge} and a_{disc} to set priorities for individual vehicles to be charged before departure time. In this case, the corresponding a_{charge} value will take a value lower than 1, if we set the a_{plug} value to 1.

5.1.3 Scalability

The above minimization cost function keep tracks of three qubits for each mall battery unit plus a couple of qubits for each vehicle contemporaneously present in the mall parking. Considering the worst situation in the data provided that occurs on Saturday at 16, we reach 30 qubits for ten mall batteries unit plus 105 qubits arising from the presence of 35 vehicles, summing up to 135 total qubits, that can be considered an intermediate number of variables for the D-Wave Annealer and a large number of variables for available free access gate model quantum processing units. If we restrain ourselves to consider a lumped battery model for the mall battery, we will end up with 108 variables.
For the QAOA demo, we have brutally shrunk the vehicle histogram by dividing the histogram by four.
So, a realistic case can be already mapped on a Dwave annealer of 5000 qubits, performing a optimization run each half an hour (that means 336 runs per week). For the gate model implementation, we should wait for next generation IBM qpu or for the implementation on a photonic qpu of more than 200 qubits to display a real world use case.

5.1.4 Results

We considered both Gate model based QAOA and D-Wave annealer implementation for our study. The version of the cost function we have implemented, considering different quadratic and linear terms on different hardware, depends on the type of behavior of the hardware. In general Qiskit IBM libraries for optimisation behave like conventional CPLEX libraries, you can provide values in the double precision range and the problem is transformed in a suitable way to be mapped on qubits.
As far as the Dwave annealing is concerned, if you choose to work with conventional solvers the behavior you get is like a fixed precision hardware, the programmer is in charge of skimming the terms in order to include only those who have a macroscopic effect in the optimisation. QAOA results were evaluated only in local BasicAer simulator and in the qasm-simulator using a qiskit runtime for the large cases, anyway the available qubits in the simulators do not allow to perform realistic calculations yet.
In general Cplex and QAOA results display the same behavior for the cases we have considered with a low number of binary variables.
As far as the implementation of mall battery optimization is concerned, we simulated the mall battery contribution for the optimization, in order to have a simpler model to check the formulation. We present in figures 9 and 7 the results for battery charging and discharging process of the lumped mall battery and for the 10 battery array depicted in the above section. In figures 6 and 6 we have the respective production of CO2 for the two scenarios.

From the output of the optimization we see that for the charging process a fine tuning of the scalars corresponding to the priority is still needed, in order to get a gradual charging process that does not affect the production of CO_2.
For the lumped mall battery scenario, dwave implementation shows slightly different values, but qualitatively the solution is similar.
More work should be paid to adjust the values for the vehicle priorities to get a good result.

5.1.5 Comparison with conventional computations

As far as the comparison with conventional computations, QAOA qiskit implementation was compared to IBM CPLEX solvers and Dwave implementation was compared to the exact solver and the simulated annealing available in the dwave ocean SDK. In general, if you add different constraints you tend to loose the convexity of the objective function and this implies that the optimisation problem is not solvable in conventional solvers like CPLEX. For gate model based QAOA one of the tight constraints was utilizing a free quantum resource in order to get a fast calculation. Available quantum simulators like the *qasm_simulator* support 30 qubits but, to avoid time overhead caused by the iterative nature of the QAOA algorithm, it is mandatory to use a Qiskit runtime to reduce latency arising from the fact that each qpu access is queued before execution.
As far as the exact solver is concerned, using it causes very long computational times, thus its adoption is strongly discouraged in cases in which the number of qubits is larger. The simulated annealing solver is quite faster than the exact solver but the final solution might display a local minimum instead of the global minumum of the computation. The quantum annealer can be used with both LeapHybrid samplers and DWave conventional samplers, but using the former exploits a large part of the available credits, so it is strongly advised to use conventional samplers as the number of qubits of the instantaneous optimization is far below 2000 qubits, so the problem can fit on both Chimera and Pegasus topologies. Moreover, the graph associated to the problem is not complete, thus the problem might not suffer from limited embedding capabilities of current QPUs.

5.2 Time Integral Optimization

5.2.1 Motivation

In this section, we propose a time integral cost function optimization which enables the use of full data simultaneously. This approach is worth exploring since the cost function has access to 'past' and 'future' conditions.

5.2.2 Mathematical Statement: Cost Function

The main idea is to optimize the emission for a large duration of given data. Ideally, it should done for the whole week, but considering the hardware limitations, we chose to solve for a day at a time, 7AM to 10PM, to be more precise. The time from 10PM to 7AM is considered dormant as not much is happening then i.e. no solar, no cars and hence the decision making/scheduling is pointless. This also helps in reducing the number of variables and constraints in the mathematical definition of problem statement.

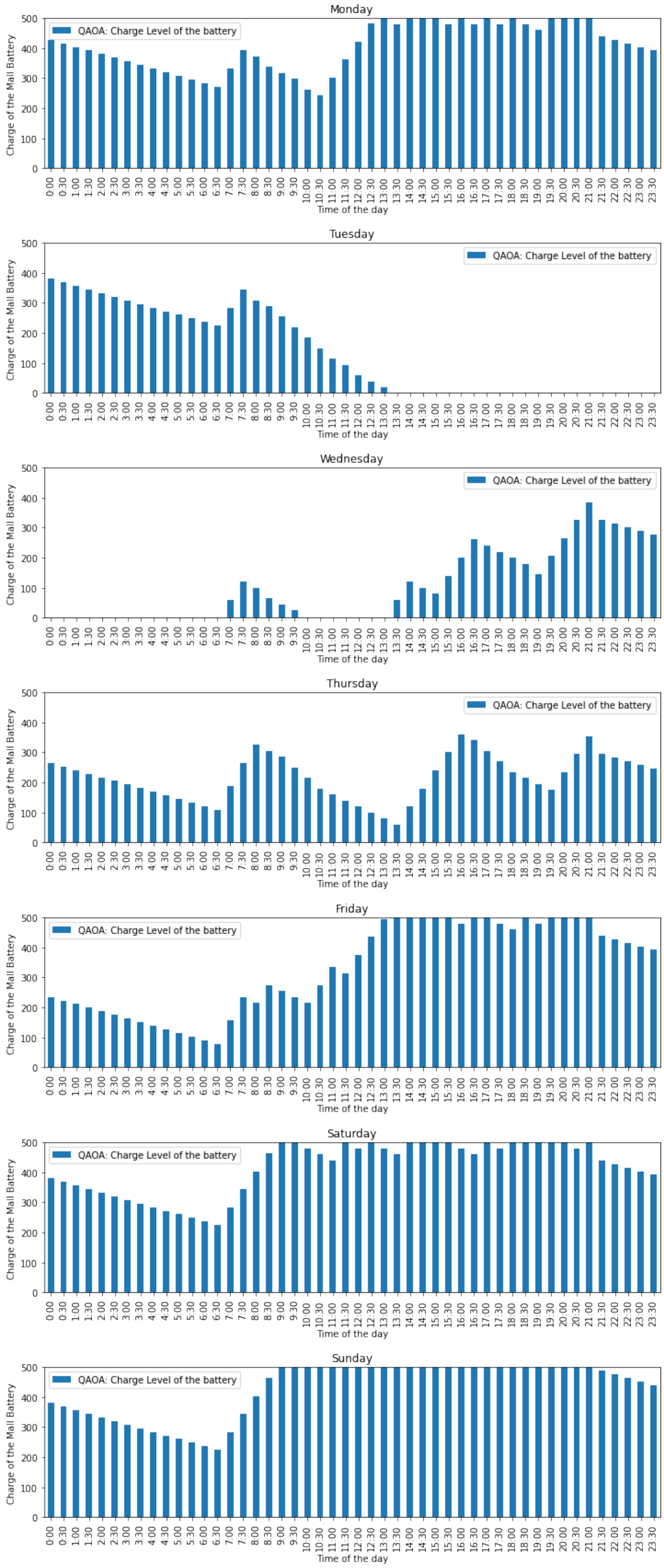

Figure 5: Lumped battery charge over weekdays for the no vehicle case, evaluated with QAOA on basic-aer quantum instance.

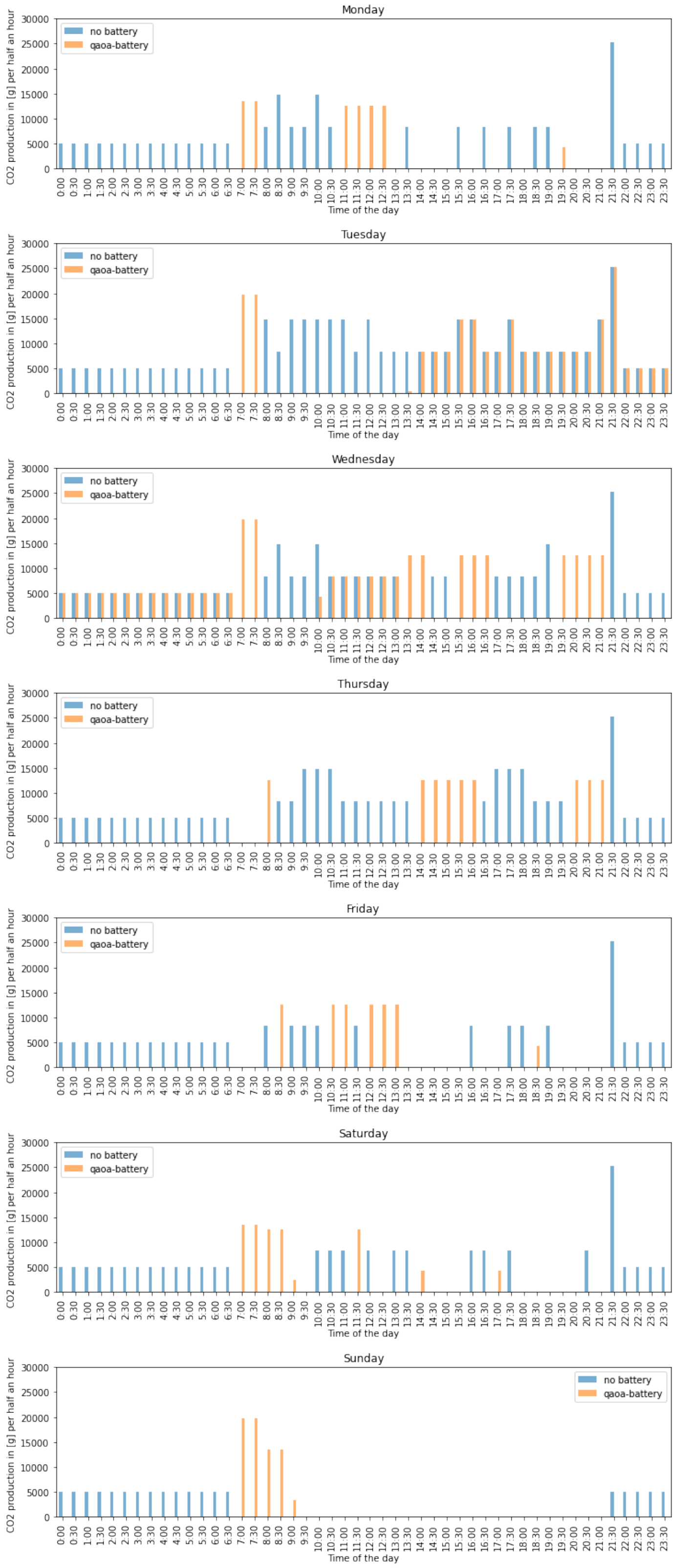

Figure 6: CO2 production for the lumped mall battery charge over weekdays for the no vehicle case, evaluated using QAOA over BasicAer quantum instance, compared to the CO2 production case with no mall battery and no vehicles.

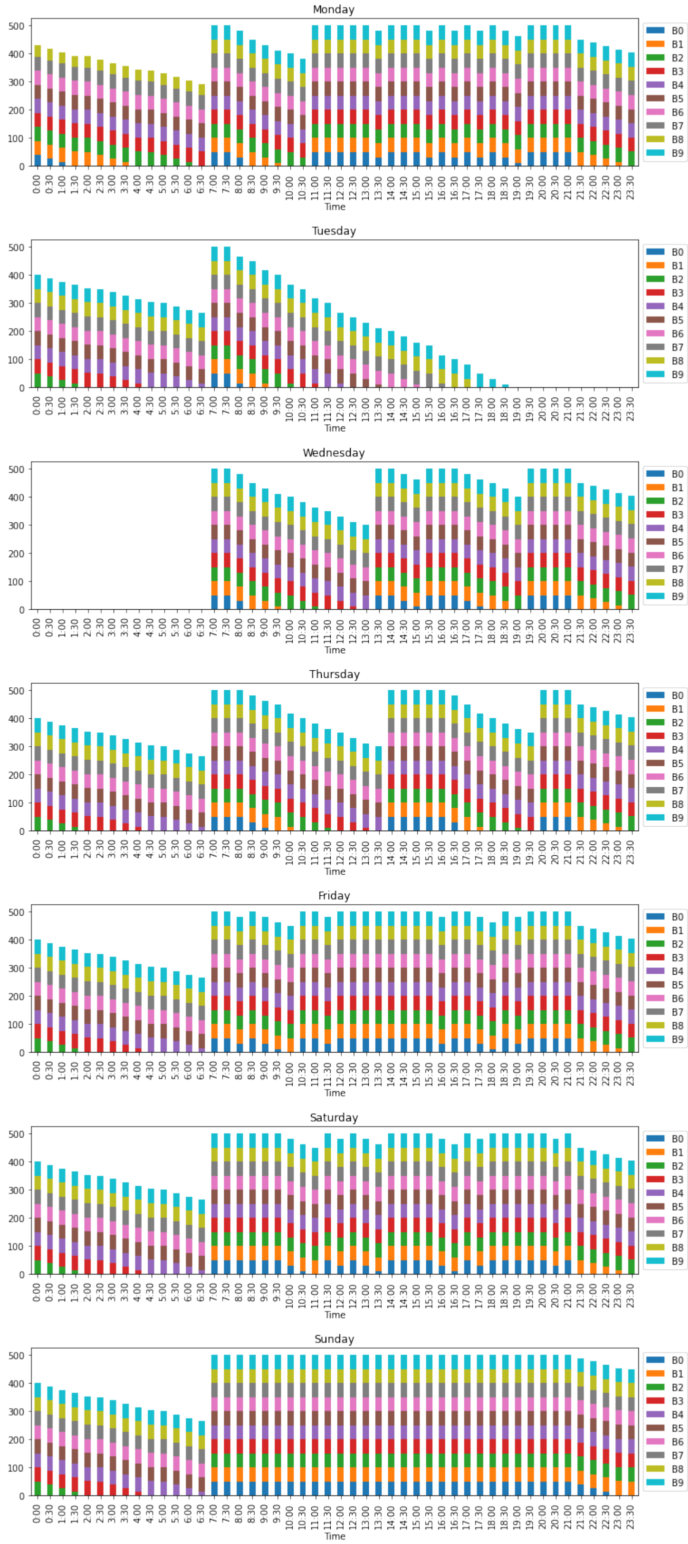

Figure 7: Ten mall battery array charge over weekdays for the no vehicle case, evaluated by cplex conventional solver (nqubits=30), compared to the CO_2 production case with no mall battery and no vehicles..

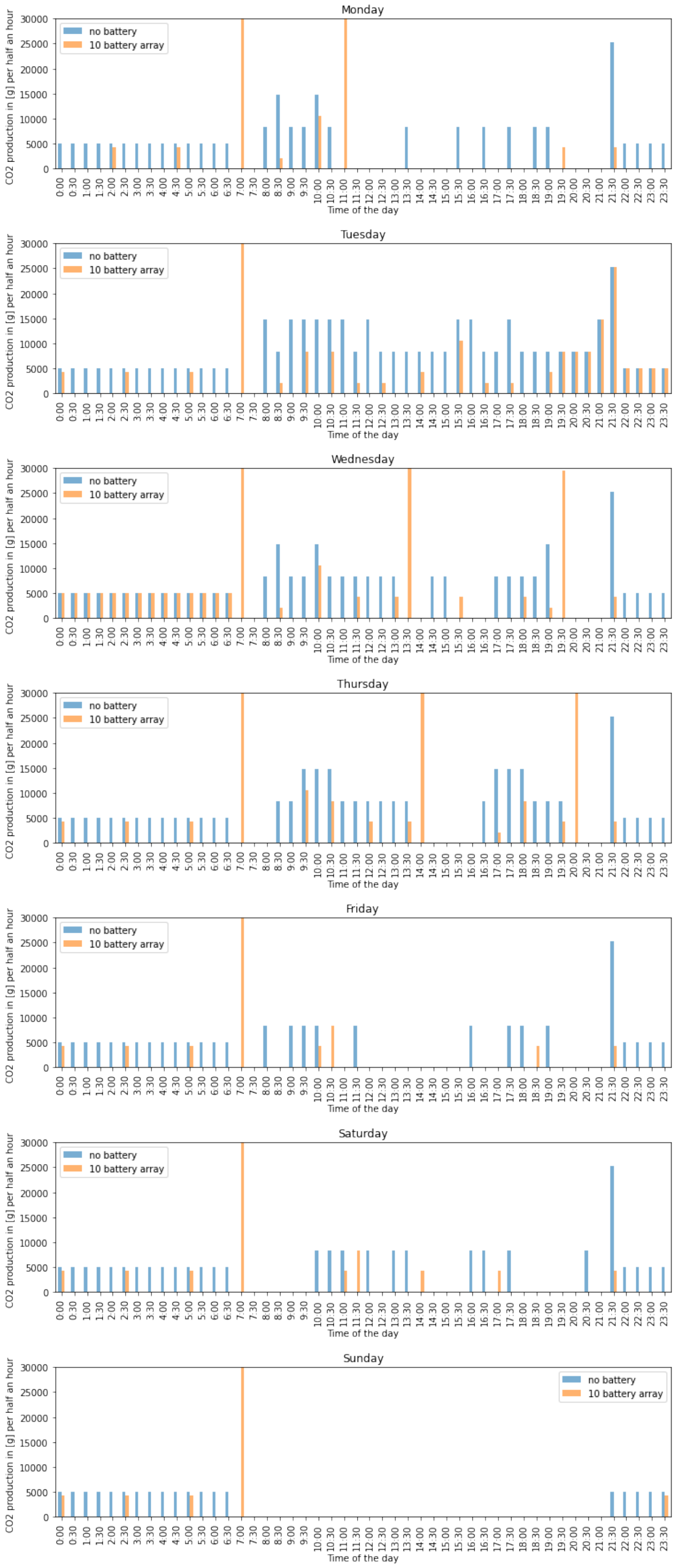

Figure 8: CO2 production for the ten mall battery charge over weekdays for the no vehicle case, evaluated by cplex conventional solver (nqubits=30), compared to the CO2 production case with no mall battery and no vehicles.

The cumulative CO_2 emission for the time under consideration is given by,

$$
\begin{aligned}
f = \sum_{i=1}^{T} \Bigg(& c_{plug} E_{plug} + c_{sol,dir} E_{sol,dir}(i) + \\
& c_{mall} \sum_{k=1}^{M} \left(\tau_{mall,disc}(i,k) + \tau_{mall,char}(i,k)\right) E_{rate}(k) + \\
& c_{car} \sum_{k=1}^{M} \sum_{j=1}^{N} K(i,j) E_{rate}(k) \left(\tau_{car,disc}(i,j,k) - \tau_{car,char}(i,j,k)\right) \Bigg) \Delta t
\end{aligned} \tag{30}
$$

Now using energy balance,

$$
\begin{aligned}
& E_{plug}(i) = E_{mall}(i) - E_{sol,dir}(i) - \\
& \sum_{k=1}^{M} \left(\tau_{mall,disc}(i,k) - \tau_{mall,char}(i,k)\right) E_{rate}(k) + \\
& \sum_{k=1}^{M} \sum_{j=1}^{N} K(i,j) E_{rate}(k) \left(\tau_{car,disc}(i,j,k) - \tau_{car,char}(i,j,k)\right) \Bigg) \Delta t
\end{aligned} \tag{31}
$$

This is then substituted in cost function to get,

$$
\begin{aligned}
min \Bigg(\sum_{i=1}^{T} \Bigg(& c_{plug} E_{mall}(i) + (c_{sol,dir} - c_{plug}) E_{sol,dir}(i) + \\
& (c_{mall} - c_{plug}) \sum_{k=1}^{M} \left(\tau_{mall,disc}(i,k) - \tau_{mall,char}(i,k)\right) E_{rate}(k) + \\
& (c_{car} - c_{plug}) \sum_{k=1}^{M} \sum_{j=1}^{N} K(i,j) E_{rate}(k) \left(\tau_{car,disc}(i,j,k) - \tau_{car,char}(i,j,k)\right) \Bigg) \Delta t \Bigg)
\end{aligned} \tag{32}
$$

Here, $c_{sol,dir} = c_{mall} = 0$, i is the time index, j is car index and k in charging/discharging rate index. Having multiple values of charging/discharging rates is a feature implemented in this function. This is expected the give the cost function more degrees of freedom to minimize the emission.

5.2.3 Mathematical Statement: Constraints

The first constraint is about the value of E_{plug}. It has to be semi positive definite in order to ensure that we get feasible results. Otherwise, a very high emission constant multiplied by a negative number would lead us in an undesired direction. Physically, this is similar to having a very lucrative option of selling the extra energy back to grid, which is not considered as part of the problem.

$$
E_{plug}(i) \geq 0, \quad for\ i = (1, 2, ..T) \tag{33}
$$

No battery is allowed to charge or discharge simultaneously. For mall battery,

$$
\begin{aligned}
& 0 \leq \sum_{k=1}^{M} (\tau_{mall,disc}(i,k) + \tau_{mall,char}(i,k)) \leq 1 \\
& for\ i = (1, 2, ..T)
\end{aligned} \tag{34}
$$

For car batteries,

$$0 \leq \sum_{k=1}^{M} (\tau_{car,disc}(i,j,k) + \tau_{car,char}(i,j,k)) \leq 1 \tag{35}$$
$$for\ i = (1, 2, ..T)\ and\ j = (1, 2, ..N)$$

Integral approach also enables easy tracking of the battery levels. The main criteria for batteries is that they must always be between 0 and 100% of the rated capacity. For mall batteries,

$$MIN \leq \sum_{l=1}^{T} \sum_{i=1}^{l} \sum_{k=1}^{M} (-\tau_{mall,disc}(i,k) + \tau_{mall,char}(i,k)) E_{rate}(k) \Delta t \leq MAX \tag{36}$$
$$for\ i = (1, 2, ..T)\ and\ j = (1, 2, ..N)$$

The MAX value is always 500 kWh and MIN value must be 0 except for last time slot. Since we are not simulating the night time (10PM to 7AM), we can ensure that the mall battery at last slot is sufficient to supply the mall for 9 hours with 24 kW i.e. 216 kWh. In this way, we simulate the whole day. Here, the initial charge in mall battery is assumed to be zero.
A similar equation is also considered for each car with minor modifications. The cars arrive with a known battery charge and they have a minimum departure battery. These facts can be easily integrated in above equation. To avoid repetition, this equation is not shown here.

5.2.4 Scalability

For simulating 7AM till 10PM with a Δt of 30 min and considering all cars on Monday, we get around 2048 variables and 798 constraints. This suggests that once the code is refined, it is easily scalable since Dwave hardware supports even more number of variables and constraints. We have developed a python code for this approach but were unsuccessful in running it on the Dwave hardware (solver). We tried using hybrid CQM and BQM solvers but could not resolve the issue. For demonstration purpose, we are presenting the results from a classical solver (simulated annealing) in next section.

5.2.5 Results and Discussion

The bistream output from solvers is post-processed in the python code. It plots all the data in a single figure, which is easy to visualize and interpret. A sample result of simulation for Monday with Δt of 30 min and 20 cars (randomly selected assuming uniform distribution) is shown below,
The figure can be easily observed to violate the constraints e.g. avoiding simultaneous charging and discharging. Unfortunately, we could not resolve this in the given time frame and future work is required to narrow down problem and improvise.

6 Executive Summary

This section provides analysis and projection of Qrious's impact, feasibility, scaling over the next 7 years across 7 key markets, 3 continents. We calculate our solutions' impact against current data of total C02 emissions, supermarket average energy cost (based on data by challenge), and industry standard rate cost and impact of EV charge/discharge. Competitor, market analysis, marketing and business opportunity strategies, and application that impacts the quantum community beyond specific business cases have also been derived and included in presentation. Results of impact, scaling, and financial analysis reflects highly promising prospects for Qrious's solution.

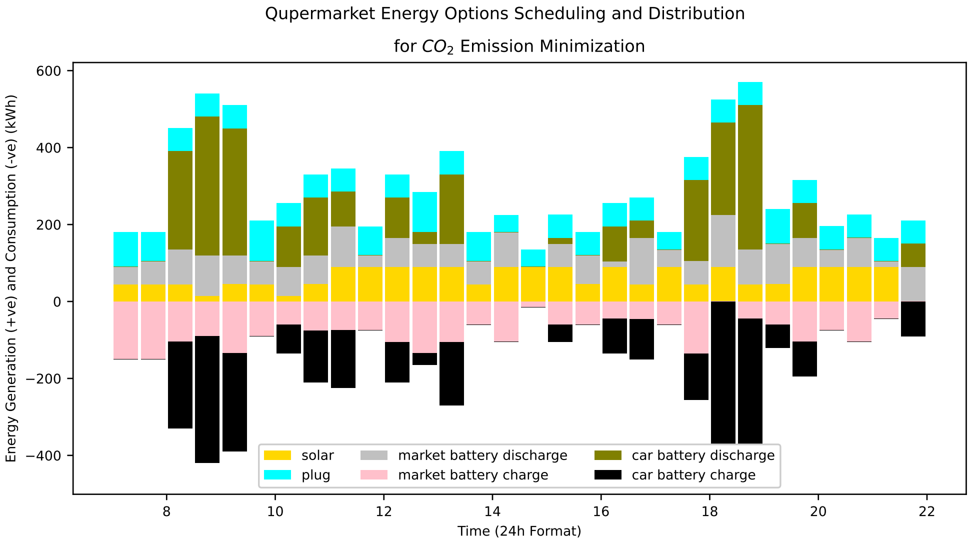

Figure 9: Summary of scheduling of available energy options for 15 hours of active operations

6.1 Scaling

Our conservative projection of only three super brands within sample markets already provide up to 24,961 stores, 200 charging stations per store. There is massive opportunity, considering Qrious solution is applicable to other super brands as well as markets (e.g. high growth EV opportunity in SEA), and even more to other businesses such as food delivery services or hospital parking spaces, ranging towards the tens and hundred thousand more in location numbers. Sample markets are chosen based on (1) key country given by challenge (Germany) (2) markets similar to key country and with high EV adoption rates (3) key markets of chosen super brands. Given the lack of previous quantum implementation, we plan to launch on few stores per market, starting in Germany then in 2 more markets for comparison within the first year. Competition concern over the combined value of total Aldi Schwarz Group stores is resolved with the potential of replacing one competitor with another supermarket that isn't in direct competition.

6.2 Financial

Financial projection derives a net present value to showcase potential investors and partners not only the impact but also profitability, discount period and financial breakdowns of our solution. Final numbers are based on (1) pricings of servers used by our solution (e.g. DWave, IBM, Amazon Braket), (2) industry average rates for revenue, taxation, trademark, depreciation, (3) total costs and time cost of charging/discharge station implementation and maintanence, quantum training, hardware application if needed.

7 About team Qrious

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