Quantum City Challenge

Applying quantum technology and solutions to Alberta’s energy industry

About the Quantum City Challenge

Quantum City is hosting an online challenge to demonstrate/assess the ability to solve problems in Alberta's energy industry with quantum technology. Quantum City is working with Amazon Web Services (AWS) to facilitate this challenge and has received sponsorship from two Alberta-based energy organizations to demonstrate the applicability of quantum solutions for modern energy industry organizations.

Approach

We understand that quantum computing is a new technology and that currently, available quantum computers are severely restricted by limitations on number of qubits, connectivity, error rates, and so on. The scale of the problem presented in this use case is far beyond what is possible for quantum computers today. This competition intends to solicit new ideas of how to apply future quantum computers to solving such industrial (even if simplified) problems. For this reason, we welcome submissions including any of the below:

- Proof of concept solutions, on a smaller and perhaps simplified problem, including a formulation and/or implementation and/or resource estimates, solved on a currently available quantum simulator and/or actual quantum device.
- Hybrid quantum-classical solutions to the full problem or a subset of it, including formulation and/or implementation and/or resource estimates, solved using a currently available simulator and/or actual quantum device, or using a stand-in for a quantum computer to solve subproblems of a type that quantum computers might one day solve efficiently, such as SAT, MaxSAT, MIP, etc.

Purpose

ATCO proposes the following problem statement for the Quantum City Challenge and welcomes efficient and novel quantum solutions for smart charging of passenger electric vehicles (EVs).

Background

ATCO remains committed to sustainability initiatives and the implementation of smart technologies aimed at assisting customers in effectively managing their energy requirements and monitoring usage. Our commitment to these endeavors is well-documented in our annual review and sustainability reports[i,ii].

We are interested in exploring the current capabilities of quantum computing and gaining insight into its future potential. Our SpaceLab team has formulated the following hypothetical test case to support this exploration of quantum computing and develop better solutions for sustainability issues.

High-Level Problem Statement – Smart Scheduling of EV Charging

For the purposes of the Quantum City Challenge, we envision a hypothetical/mock city (the "city") with the following characteristics: the city has experienced substantial adoption of EVs; the city is a densely populated urban area where access to home charging is relatively limited, so the development of public charging infrastructure is necessary to facilitate EV charging, and the city has determined it will build an independently powered hub of publicly available EV charging stations (the "charging hub") to meet the charging needs of EV owners.

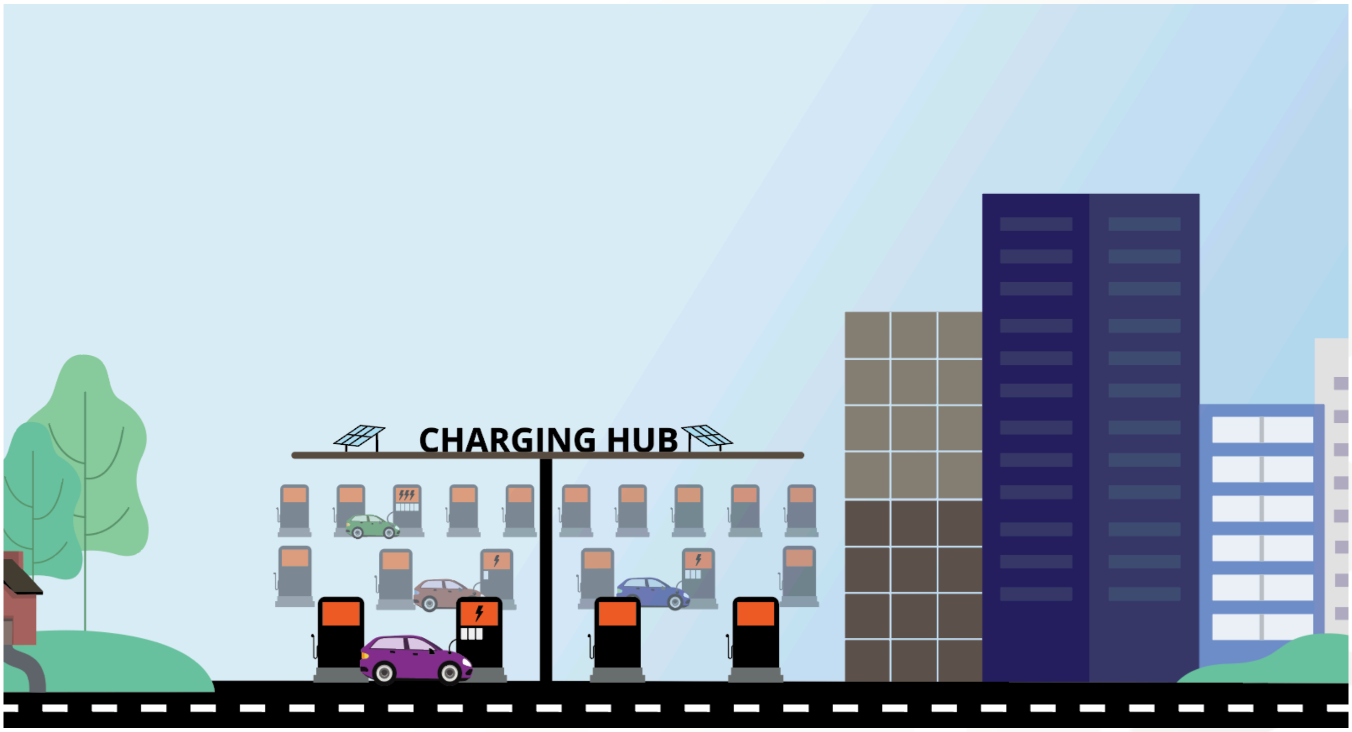

Figure 1: A visual depiction of the city with the charging hub catering to the needs of the EV owners.

The city does not yet know how it will avoid exceeding the electricity supply constraints of the charging hub, but knows that it will need to balance the charging hub supply and the EV charging demand, the charging time preferences and the schedule of each EV owner. The smart scheduling of the EV charging problem (the "city problem" and a "combinatorial optimization problem") is closest to the mathematically defined weak NP-hard space[iii], and the city is interested in exploring whether quantum computing may provide advantages over classical computing[iv]. The city welcomes quantum solutions that demonstrate the potential of better performance of quantum approaches vs. classical state-of-the-art solutions[v].

Figure 2: A busy EV charging station with arriving, charging and departing EVs with varying charging levels.

Previous Classical Approaches

Similar optimization problems have been approached in multiple ways previously[vi,vii,viii,ix]. Even within the relaxed constraints of the city's problem formulation provided in this problem statement, the combinatorial optimization problem remains a formidable challenge for quantum approaches[x]. Most classical algorithms tend to be computationally expensive, with their computational times scaling exponentially with the number of variables in the model.

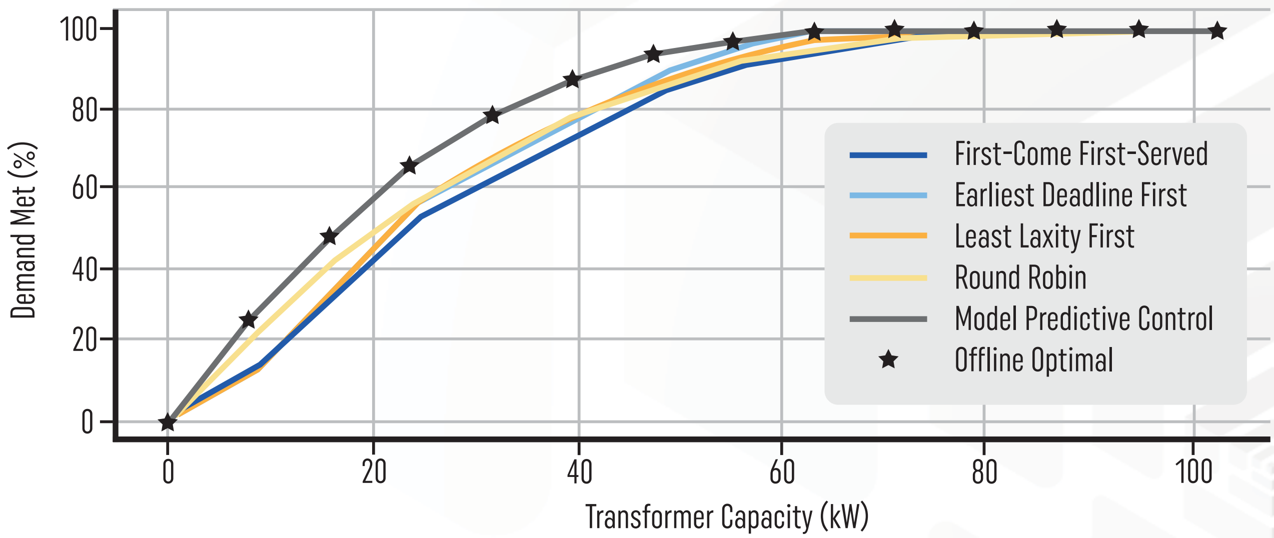

Figure 3: The classical scheduling algorithms in comparison with Model Predictive Control being the adaptive or smart scheduling algorithm. The smart scheduling algorithm shows better performance by meeting the maximum demand in theory compared to other traditional algorithms[ix].

The city's problem has been intentionally simplified to be solvable by a limited number of qubits, with the assurance that classical optimization solutions are readily accessible. Models for scheduling charging in classical computing exist in the literature, have undergone a few pilot tests and commercial products have been released as well[v,xi,xii]. For the purposes of the Quantum City Challenge, we will consider Model Predictive Control (see Figure 3) – or a similarly performing solution to be the state-of-the-art classical solution.

Solution Requirements

Each quantum solution proposed for the city problem must indicate how it compares against at least one of the classical models referred to in the Previous Classical Approaches section above. The solution metrics should include the computational time and optimization accuracy metrics, total energy demands met, a graph showing the hourly energy delivered throughout the day, along with varying levels/parameters of optimization. We expect details about the hardware usage, the quantum noise measured, and error-related specifics observed so that we can gain a deep understanding of how each solution uniquely addresses quantum capabilities for optimization problems like the city's problem.

We observe that some studies offer potential applications for quantum computing in sustainability-related areas[vi-x], but note that at this early stage in the development of quantum computing, the advantages provided by quantum computing, in comparison to classical algorithms, for solving optimization problems are unclear. Each quantum solution proposed must include a discussion about prospective advantages of future quantum computers for solving optimization problems of this type.

Data Sources

The city has provided all the necessary information for the participants, including the mathematical problem formulation, the mock datasets and the precise optimization objective functions, which form the "Detailed Problem Statement" section. The mock scenario and data have been generated using Statistics Canada data and other publicly available data sources[xiii,xiv,xv,xvi,xvii,xviii].

Technical Glossary:

For participants' reference, the city provides the following glossary. If participants are interested in more detailed information about terms used in the electricity industry, they can refer to the referenced material[xix]. These terms are used in the Detailed Problem Statement that follows:

- **Ampere (A):** a unit of measure of electric current. An ampere is equal to an electric current flow of one coulomb per second.

- **Charge:** denotes the energy requested by an EV owner.
- **Charging variables:** denotes the electric current and the pending electric energy delivered from the charger to the EV's batteries, at a given time-step.
- **Charging hub:** the city's independently powered charging hub comprised of the charging stations.
- **Direct Current Fast-Chargers:** are EV chargers that use a 480 Volt system. These chargers can charge an EV's battery to 80% in 30 minutes. Also known as Level 3 chargers.
- **Electric current:** rate of flow of the electric charge going from the charger to the EV.
- **EV:** passenger electric vehicle.
- **Energy:** electrical energy is energy stored in an electric field or transported by an electric current.
- **KiloWatt (kW):** a thousand Watts.
- **KiloWatt-hour (kWh):** a thousand Watt-hours.
- **Level 2 chargers:** EV chargers that offer higher-rate AC charging through 240V or 208V electrical service, and are common for home, workplace, and public charging. These chargers can charge an EV's battery to 80% in 3-10 hours.
- **MegaWatt-hour (MWh):** a million (10^6) Watt-hours.
- **Power:** the rate at which the electric circuit can transfer electrical energy. It is equal to the product of electric current and voltage.
- **The city:** hypothetical city in this problem statement.
- **Total load:** the hourly cumulative energy delivered by the charging hub for all the EVs.
- **Voltage:** the pressure that causes the electrons and thereby electric current to flow through a circuit.
- **Volt (V):** a measure of voltage. One volt is the difference of potential energy that drives one ampere of electric current.
- **Watt (W):** a unit of power. One watt is equal to one joule per second and is the same as the power in an electric circuit with a potential difference of one volt and the electric current of one ampere.
- **Watt-hour (Wh):** a unit of electrical energy. One Watt-hour is equivalent to the energy used/transferred at a power of one Watt in one hour.

Detailed Problem Statement:

The city currently has a total of 25,000 EVs and the public charging hub introduced previously. The city has planned the details of the charging hub and their respective charging capacities based on the assumptions below.

It is important to note that the city's problem formulation includes certain simplifying assumptions. For instance, the city assumes that the EVs are personal vehicles primarily used for work commutes and is not interested in exploring charging for commercial vehicles. The city also assumes a uniform energy pricing structure for all hours of charging, with no demand pricing (an additional charge based on maximum power draw).

Additionally, the city is not interested in: i) any consideration of vehicle-to-grid (or V2G) functionality; ii) distribution system losses, equipment impacts, or congestion; or iii) complexities related to three-phase charging. Consequently, the city assumes that the public charging hub exclusively offers Level 2 chargers, with the absence of direct current fast chargers.

The Demand:

1) Based on the city's census data, the total number of EVs commuting for the employed labor force (excluding carpooling and public transiters) is 25,000 with an average one-way commute time of 27.70 mins.
2) The city uses as a working assumption an average EV efficiency of approximately 0.2 kWh per kilometer and an average driving speed of approximately 50 kilometers per hour. This results in an estimated energy requirement of 4.618 kWh for an average one-way commute for each EV. Therefore, the expected daily two-way commute requires approximately 9.236 kWh.
3) With an average EV battery capacity of 50 kWh, each commute consumes on average one-tenth of a full battery charge[xvii]. Consequently, each EV will require a recharge approximately every 5 days. Assuming an equal distribution of charging needs, one-fifth of the commuters (5,000) charge their vehicles daily. Considering that some EVs may need minimal top-ups (2,000 per day), a total of 7,000 EVs are expected to come to the hub for charging every weekday. To account for any unforeseen demand or accelerated battery drain resulting from winter weather, the city assumes a consistent influx of 7,000 EVs seeking a charge, even during weekends.
4) The maximum daily energy requirement can be calculated as follows: 7,000 EVs x 50 kWh = 350,000 kWh or 350 MWh. If the charging is evenly distributed throughout the day, there would be an additional load of 14.5 MWh per hour. It is important to note that this scenario represents an ideal situation, as real-time demand tends to be higher during the 8 am to 6 pm window and lower after 6 pm, as explained under (6).

The Supply:

5) Based on the requirements gathered above, the city's charging hub is designed with 30 charging stations. Each charging station is equipped with 100 Level 2 charging ports. It is worth noting that Level 2 chargers have the capability to deliver up to 20 kW, which is the upper bound on supply from each charging port.
6) The city utilized the arrivals data from the ACN-Dataset[xv] (see Figure 4) to calculate hourly demand, which was then scaled up to account for 7,000 EVs (comprising 5,000 EVs requiring a full charge and 2,000 requesting top-ups). We have provided the hourly arrival numbers for charging in the provided file (EVArrival_time.xlsx), for weekdays and weekends in separate tabs.

For the full charge requests, on weekdays, the average available charging time is assumed to be 6 hours, while on weekends, it is assumed to be 4 hours. For top-up requests, consider a charging time of only one hour on both weekdays and weekends. Given that the charging time typically ranges between 4 to 6 hours, the city recommends an optimization horizon of greater than 6 and less than 12 hours.

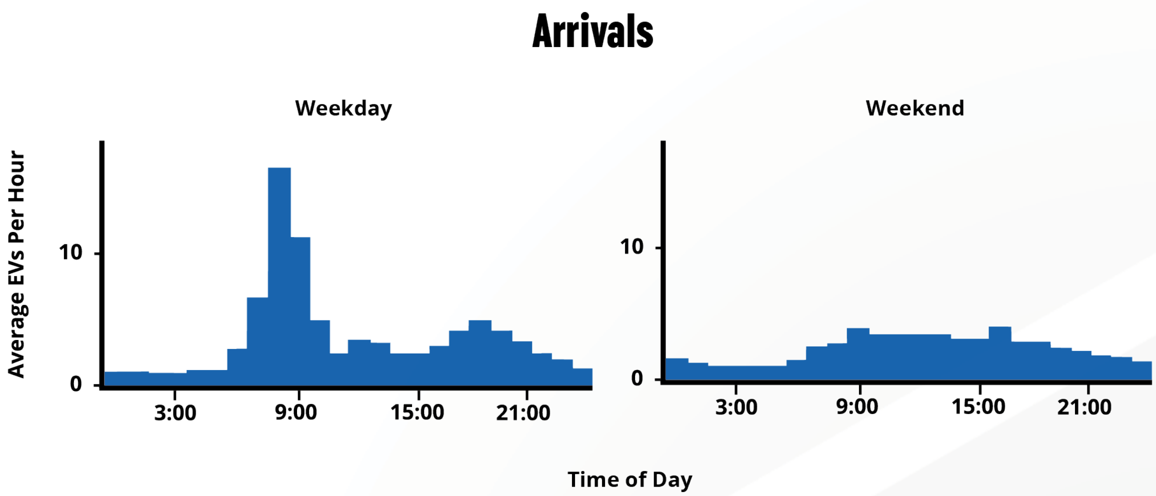

Figure 4: Graphs showing the arrival time distributions of EVs over the duration of 24 hours from the reference[ix].

Mathematical constraints:

Consider a consistent voltage of 240V for the Level-2 chargers, with electric current varying between 0 and 64A. This configuration results in a maximum power output of 15.36 kW.

Let $r_i(t_k) \in \rho, \forall\, i, t_k$ be the electric current at which the i^{th} EV will be charged at time t_k. Here, ρ represents the set of allowed, discrete charging electric currents. For Level-2 chargers, industry standard defines the set ρ as $\{8, 16, 32, 48, 64\}$ A. Time is discretized into steps of size Δt (=15 minutes or 30 minutes), such that each discrete time-step is denoted by t_k, where $1 \leq k \leq n$. Therefore, n is the number of time steps in the optimization horizon, which has a total duration of $n\Delta t$. The first time step of the optimization horizon starts at t_1 and the final time step of the optimization horizon starts at t_n. For convenience, T will denote the end time of the optimization horizon, so that $T = t_n + \Delta t$.

As a check to ensure that the supply from one charging port would meet the maximum demand of one EV within 6 hours: an EV requires 50 kWh for a full charge, and the maximum draw from a port is 15.36 kW (=64A*240V), indicating that in 6 hours, it should deliver approximately 90 kWh, nearly double the required amount.

The maximum number of EVs requiring a full charge at any given time is less than 2,500 and those requiring top-ups of 10kWh are less than 400. This ensures that the available number of ports (3,000) exceeds the maximum number of ports demanded at any given time. The requested charge for each EV is denoted by e_i and the adjusted remaining charge at the beginning of each time-step is $e_i(t_k)$, where k is the time-step index.

The city requires the EVs to always be in a state of charging from when the EV plugs in until its charging demand is met:

$$r_i(t_k) \in \rho \; if \; e_i(t_k) > 0, \qquad \{0\} \; otherwise$$

This constraint helps prevent contactor wear in the EV charging ports.

The set ν_{t_k} denotes the active EVs plugged in for charging at a given t_k (ν_{t_k} will need to be updated at each time-step) and the quantum algorithm should solve for the set of electric currents at which each EV needs to be charged: $r_i(t_k), i \in \nu_{t_k}$ over the optimization horizon. While the optimization horizon is fixed, please note that the available charging time (η_i) for each EV is different. For concreteness, if we denote the arrival time of EV i as $\tau_i^{arrival}$ then the end of the available charging time is denoted by $\tau_i^{end} = \tau_i^{arrival} + \eta_i$. For full charge requests, η_i must be taken as 6 hours on weekdays, 4 hours on weekends and 1 hour for top-ups on any day as mentioned in the Supply section.

As an example, consider an optimization horizon of 6 hours starting at $t_1 = 12{:}00$ pm, and ending at $T = 6{:}00$ pm. For each EV requesting a full charge, the charging end time is given by: $\tau_i^{end} = \tau_i^{arrival} + 6 \; hours$. Now consider the EV's that arrived earlier between $7{:}00$ am and $11{:}00$ am that requested a full charge. For an EV with $\tau_i^{arrival} = 7{:}00$ am the charging end time will be $\tau_i^{end} = 7{:}00 \text{ am} + 6 \; hours = 1{:}00$ pm. Therefore, when the first time-step of the optimization horizon begins at $12{:}00$ pm that EV will be counted in ν_{t_k} and have 1 hour more to be charged. Consider $\Delta t = 0.5 \; hour$ and at the third time-step starting at $1{:}00$ pm, the EV that started charging at $7{:}00$ am, will be removed from ν_{t_k}, while the EVs that started charging between $8{:}00$ am and $12{:}00$ pm will still be included in ν_{t_k}. As demonstrated, t_1 and T are fixed for an optimization horizon, but $\tau_i^{arrival}$ and τ_i^{end} can be outside the time limits of the optimization horizon and are different for each EV.

During each optimization, the quantum algorithm must solve for the optimization variables ($\hat{r}$) for all time-steps within the optimization horizon. The algorithm needs to update the time-step index (k) as time-steps increase and update the pending energy requested ($e_i(t_k)$) based on the cumulative charging completed until the k^{th} time-step:

$$e_i(t_k) = e_i - \sum_{j=0}^{k} r_i(t_j) * V * (t_j - t_{j-1}), \qquad i \in \nu_{t_j}, V = 240 \; volts$$

A sample pending charge calculation at the k^{th} time-step using the above equation: Assume the i^{th} EV requests a full charge: e_i = 50 kWh and Δt = 30 minutes (0.5 hour). At k=7, if the algorithm used 32A to charge the EV for the past 3 hours: the EV will have been charged for 23.04 kWh (=240V*32A*3h) and so the pending charge $e_i(t_7)$ would be 26.96 kWh (=50-23.04kWh). The quantum solution must solve for $\hat{r}$ for the k^{th} time step and update the pending energy $e_i(t_k)$, and similarly for the succeeding time steps. In essence, the solution would provide the optimized charging variables (both the electric charging current and the pending energy). This iteration should continue till the departure time of the EV.

$$r_i(t_k) \in \rho, \qquad t_k < \tau_i^{end}, \qquad i \in \nu_{t_k}$$

$$r_i(t_k) = 0\,, \quad t_k \geq \tau_i^{end}, i \in \nu_{t_k}$$

$$\sum_{j=0}^{k} r_i(t_j) * V * \Delta t \;\leq\; e_i,\; i \in \nu_{t_k}, V = 240\, volts$$

The constraints mentioned above serve several purposes: they guarantee the EVs to always be in a state of charging; prevent EVs from being charged beyond their departure times; and cap the total charging at the requested amount (50 kWh for full charge requests and 10kWh for top-up requests).

Objective functions:

The city has selected key objective functions (functions to be optimized) from previous work[vi - xii]. However, participants are encouraged to modify and experiment with the weights and parameters of each objective function.

Note: At the start of every optimization horizon, t_1 and T would need to be updated. As an example, consider an optimization horizon of 7 hours starting at $t_1 = 9{:}00$ am, and ending at $T = 4{:}00$ pm. Once $\hat{r}$ is determined for the optimization horizon ranging between 9: 00 am and 4: 00 pm, the next optimization horizon would be updated as ranging between $t_1 = 4{:}00$ pm and $T = 11{:}00$ pm. With arriving and departing traffic of EVs varying within any optimization horizon considered, the EVs plugged in for charging (ν_{t_k}) at every time step (t_k) would vary and need appropriate updates.

The initial objective is to incentivize the rapid charging of all vehicles by maximizing the following objective function (QC = quick charging):

$$U^{QC}(\hat{r}) := \sum_{k=1}^{n} \frac{T - t_k}{T - t_1} \sum_{i \in \nu_{t_k}} r_i(t_k)$$

The prefactor yields a linear reduction in reward as energy delivery extends over time – the prefactor is 1 for $k = 1$ and drops down to $1/n$ for $k = n$. This mechanism encourages the charging hub to deliver energy as quickly as possible, which helps free capacity for future EV arrivals.

The second objective function is focused on fulfilling EV owners' energy charging requirements within the available charging times, by maximizing the following expression (NC = non-completion penalty):

$$U^{NC}(\hat{r}) := -\sqrt[p]{\sum_{i \epsilon v_{t_k}} |(\sum_{k=1}^{n} r_i(t_k) * V * \Delta t - e_i)|^p}$$

When the value of p is set to 1, it indicates that there is no preference among EVs when it comes to charging priority. However, if p is increased to a value greater than 1, it results in the prioritization of EVs with higher energy requests (e_i) and shorter available charging times. To experiment with this objective, the 2,000 EVs requesting top-ups can randomly request any amount of energy between 0 and 50 kWh (instead of the set 10kWh). This objective function should demonstrate the prioritization based on the descending order of charge requests.

To minimize the total load variations, we define the net load for a given time step as:

$$N(t_k) := \sum_{i \in v_{t_k}} r_i(t_k)$$

such that the maximization of the following objective function serves to minimize total load variations (LV = load variations):

$$U^{LV}(\hat{r}) := -\sum_{k=1}^{n} N(t_k)^2$$

If the participants are interested in minimizing the total load, a linear net load summation would be the minimization objective. Imposing a strict upper bound constraint on the charging variables can also yield a similar effect (max$(\rho) = 32$ A or power equivalent, instead of 64 A).

The city suggests to aggregate the three objective functions (for example, as a weighted sum) to create an optimization objective that seeks to maximize the distribution of EV charging, while also ensuring that the EVs are charged within their available charging times and with the requested charging energy. It is worth noting that this optimization objective may not necessarily yield unique solutions, and that is acceptable. If the goal is to steer towards unique solutions, there are regularization techniques[ix] that could help, although they are not obligatory.

For those interested, please refer to the ACN simulator paper for insights into the classical algorithm, which may assist in formulating the quantum optimization setup[ix].

A demonstration of the above algorithm is contrasted against a conventional charging situation below, as an example. The area under each color contour stays the same between the two graphs (the total energy delivered to each EV).

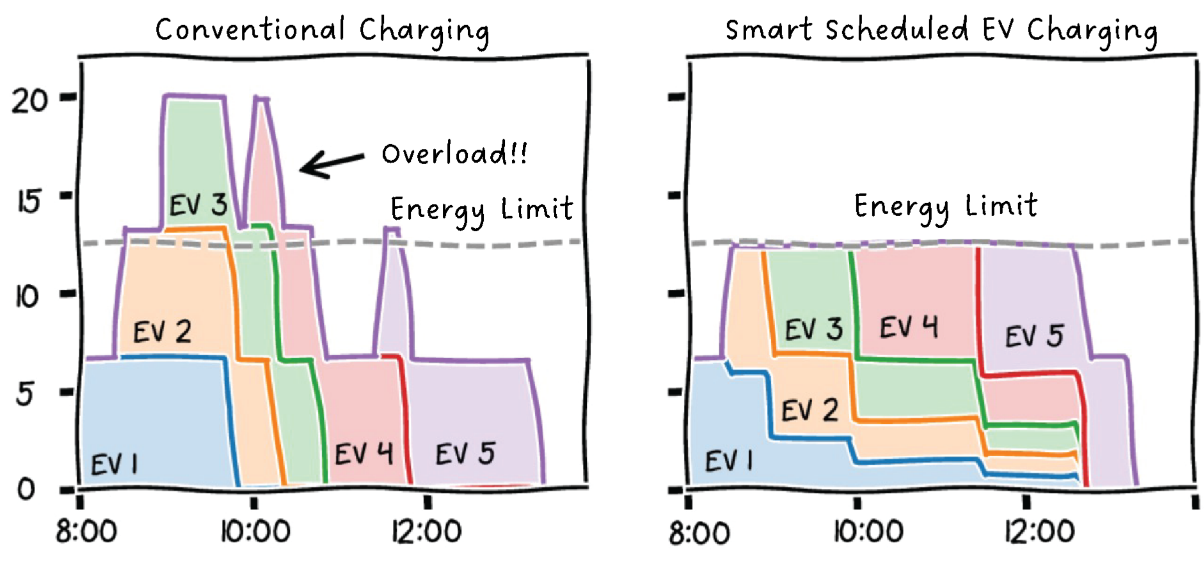

Figure 5: Charging schedule of five EVs, with delivered energy (kWh) on the y-axis and time (hours) of charging on the x-axis. This depicts adaptive charging to maximize the charging spread[ix].

Bonus Points:

Novel quantum approaches that demonstrate the ability to handle more complex scenarios than those described in the Detailed Problem Statement will be rewarded. Examples of these complexities may include optimizing within tighter charging constraints (upper limit of 32 A instead of 64 A), satisfying the demand with fewer charging stations and ports, and formulating improved objective functions to enhance optimization.

As noted above, the Detailed Problem Statement and the accompanying mathematical formulation have been intentionally simplified, featuring certain assumptions and basic objective functions for optimization. However, we strongly encourage participants to explore and experiment with the information provided in order to devise more effective quantum optimization methods capable of excelling under more realistic constraints. There are no limitations on the creative approaches participants may employ to address this challenge.

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End Notes / References:

[i] https://www.atco.com/content/dam/web/our-commitment/sustainability/2022-sustainability-report.pdf
[ii] https://www.atco.com/content/dam/web/about-us/investors/ATCO-2022-Annual-Report-website.pdf
[iii] https://www.cs.virginia.edu/~robins/The_Limits_of_Quantum_Computers.pdf
[iv] https://hbr.org/2021/07/quantum-computing-is-coming-what-can-it-do
[v] https://ev.caltech.edu/index
[vi] https://arxiv.org/pdf/2107.05362.pdf
[vii] https://arxiv.org/pdf/2012.14859.pdf
[viii] https://ev.caltech.edu/assets/pub/ACN_Data_Analysis_and_Applications.pdf
[ix] https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9509290
[x] https://arxiv.org/pdf/2007.07391.pdf
[xi] https://www.mdpi.com/1424-8220/22/8/2834
[xii] https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/May/IRENA_EV_smart_charging_2019_summary.pdf
[xiii] https://www12.statcan.gc.ca/census-recensement/2021/dp-pd/prof/index.cfm?Lang=E
[xiv] https://www.data.gouv.fr/fr/datasets/belib-reseau-parisien-de-bornes-de-recharges-accelerees-22-kw-ac-dc-pour-vehicules-electriques/
[xv] https://ev.caltech.edu/dataset
[xvi] https://www.spglobal.com/mobility/en/research-analysis/ev-chargers-how-many-do-we-need.html
[xvii] https://www.iea.org/energy-system/transport
[xviii] https://natural-resources.canada.ca/sites/nrcan/files/canmetenergy/pdf/Smart-Grid-in-Canada-2020-2021.pdf
[xix] https://mikefullerelectric.com/understanding-electrical-terms/

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