# Increased Plan Stability in Cooperative Electric Vehicles Path-Planning

**Jaël Champagne Gareau, Guillaume Gosset, Marc-André Lavoie, Éric Beaudry, Vladimir Makarenkov**

Computer Science Department
Université du Québec à Montréal
Montréal, Québec, Canada
{champagne_gareau.jael, gosset.guillaume, lavoie.marc_andre, beaudry.eric, makarenkov.vladimir}@uqam.ca

## Abstract

The Cooperative Electric Vehicles Planning Problem (CEVPP) has recently been proposed as a multi-agent variant of the Electric Vehicle Path-Planning Problem (EVPP). It consists in finding a set of paths for a fleet of electric vehicles that minimizes the global plan execution time, including the time spent waiting at the charging stations. In the proposed formulation, new Electric Vehicles (EVs) can join the fleet at any time, and a centralized planner recomputes the optimal plan every now and then to take them into account. However, the newly computed plans of EVs that were already on the road can change drastically, compared to their previous plans. In this paper, we propose an extension of CEVPP that considers the plan stability in the objective function as a way to reduce cognitive load on the human drivers. The results of our experiments, conducted with real road networks and charging stations, indicate that our approach can significantly reduce the variability of the optimal plans, while keeping low the global plan execution time.

## 1 Introduction

The Electric Vehicle Path-Planning Problem (EVPP) consists in finding a path for an electric vehicle (EV) that minimizes the time spent on the road (Sachenbacher et al. 2011; Baum et al. 2015). Some variants of the problem also consider the time spent waiting at the charging stations (Sweda, Dolinskaya, and Klabjan 2017; Champagne Gareau, Beaudry, and Makarenkov 2019). Many methods have been proposed to solve this problem efficiently when each EV is considered independently. However, when multiple EVs are considered as a whole, the problem becomes significantly more complex, as the plans of the EVs can interfere with each other (e.g., many EVs may end up waiting at the same charging station at the same time).

A multi-agent variant of EVPP, called the Cooperative Electric Vehicles Planning Problem (CEVPP), has recently been proposed (Champagne Gareau et al. 2024). It consists in finding a set of paths for a fleet of electric vehicles that minimizes the global plan execution time, including the time spent on the road as well as the time spent charging and waiting at the charging stations. In the proposed formulation, new EVs can join the fleet at any time, and a centralized planner recomputes the optimal plan with respect to a specified rule (e.g., every time a pre-specified number of new EVs join the fleet or after a predefined time interval) to take into account the new EVs in the system. However, after such a replanning, the newly computed plans of EVs that had been already on the road can change drastically.



In this paper, we propose an extension of CEVPP which takes into account the plan stability (Fox et al. 2006; Babli, Sapena, and Onaindia 2023) in the objective function. We define a stability metric in the context of multi-agent planning problems. This new metric allows one to reduce the variability of the plans, thus increasing the predictability of the system and making it easier for the agents to coordinate their actions. In the context of CEVPP, considering the plan stability can be particularly important for the human EV drivers, who might prefer a better steadiness in planning their activities in order to reduce the cognitive load associated to last-minute changes. For example, a driver could plan to stop at a specific location, such as a restaurant or a viewpoint, next to a planned stop at a charging station. If a newly recomputed optimal plan doesn't include this specific location anymore, the driver's plans may fall through. Since the preference of the drivers are not known in the model *a priori*, and can change over time after the initial plan computation, the plan stability can be considered as a possible solution limiting the variability of the plans for the EV drivers.

## 2 Cooperative Electric Vehicles Planning

In the original formulation of the Cooperative Electric Vehicles Planning Problem (CEVPP), a tuple $(\alpha, \omega, \rho, \tau)$ represents a request an EV makes to the planner, where $\alpha$ is the starting location, $\omega$ is the destination, $\rho$ is the range of the EV, and $\tau$ is the time when it joins the fleet (i.e., its departure time from location $\alpha$). When the initial plan $\pi^{(0)}$ is computed or when a replanning occurs, the objective is to find a global plan:

$$\pi^{(i)} = \left[\pi_1^{(i)}, \pi_2^{(i)}, \ldots, \pi_{n_i}^{(i)}\right],$$

where $\pi_j^{(i)}$ is the plan of the $j^{\text{th}}$ EV after the $i^{\text{th}}$ replanning, and $n_i$ is the number of EVs in the fleet at that moment.

In CEVPP, the objective function $Z$ used to measure the quality of a global plan $\pi^{(i)}$ is defined as follows:

$$Z(\pi^{(i)}) = \frac{1}{n_i} \sum_{j=1}^{n_i} \left( C(\pi_j^{(i)}) - C^\star(\pi_j) \right)^2,$$

where $C^\star(\pi_j)$ is the cost of the optimal plan for the $j^{\text{th}}$ EV when it is alone on the road network, i.e., the cost of a shortest-time plan assuming the waiting time is zero at each station. CEVPP uses the squared difference between $C(\pi_j^{(i)})$ and $C^\star(\pi_j)$ in $Z$ instead of using the makespan (maximum cost over all EV plans) or the flowtime (sum of the costs of all EV plans) because end users of a system based on CEVPP would not want to undergo a large detour to help many other end-users save a small amount of time.

The cost of plan $\pi_j^{(i)}$ is given by:

$$C(\pi_j^{(i)}) = T_r(\pi_j^{(i)}) + T_w(\pi_j^{(i)}) + T_c(\pi_j^{(i)}),$$

where $T_r(\pi_j^{(i)})$ is the time spent on the road, $T_w(\pi_j^{(i)})$ is the time spent waiting at the charging stations, and $T_c(\pi_j^{(i)})$ is the time spent charging.

The optimal plan during the $i^{\text{th}}$ replanning is found by solving the following optimization problem:

$$\pi^{\star(i)} = \operatorname*{arg\,min}_{\pi^{(i)} \in \Pi^{(i)}} Z(\pi^{(i)}),$$

where $\Pi^{(i)}$ is the set of all possible plans considering the vehicles active in the fleet during the $i^{\text{th}}$ replanning.

Since this optimization problem cannot be solved exactly in a reasonable time, an approximate planner, named *Permutations Cooperative EV Planner* (pcEVP), has been recently proposed (Champagne Gareau et al. 2024). This planner is inspired by the *Cooperative A** algorithm (Silver 2005). It considers multiple permutations of EVs and computes the plan for each EV one by one in the order given by the permutations, considering the plans of the already computed EVs as soft constraints using a reservation table that estimate the waiting times. Since each permutation may yield a different global solution, the pcEVP planner considers multiple permutations and selects the best solution found according to the objective function $Z$. While in theory, even considering all possible permutations provides no guarantee of finding the optimal solution, the pcEVP planner has been shown to find satisfactory solutions in practice, even for a subset of permutations (e.g., $\log(n!)$ of the $n!$ possible permutations).

## 3 Increased Stability in CEVPP

After the $i^{\text{th}}$ replanning, the plan $\pi_j^{(i)}$ of an EV may change drastically compared to its previous plan $\pi_j^{(i-1)}$. This may be problematic for the EV driver, who might prefer a better plan stability to a slightly faster journey. We propose in this section an extension of CEVPP that takes into account the predictability of the plans and considers the plan stability in the objective function of the method.

The objective function we propose is as follows:

$$\bar{Z}(\pi^{(i)}) = \frac{1}{n_i} \sum_{j=1}^{n_i} \left[ \left( C(\pi_j^{(i)}) - C^\star(\pi_j^{(i)}) \right)^2 + \delta^2(\pi_j^{(i)}) \right].$$

$$\begin{array}{lccccccccc}
\pi_j^{(0)} = & A_1 & \rightarrow & B_1 & \rightarrow & C_1 & \rightarrow & D_1 & \rightarrow & E_1 \\
 & & & & & \downarrow & & \downarrow & & \\
\pi_j^{(1)} = & & & B_1 & \rightarrow & C_2 & \rightarrow & D_2 & \rightarrow & E_1 \\
 & & & & & \downarrow & & \downarrow & & \\
\pi_j^{(2)} = & & & B_1 & \rightarrow & C_1 & \rightarrow & D_3 & \rightarrow & E_1 \\
 & & & & & & & \downarrow & & \\
\pi_j^{(3)} = & & & & & C_1 & \rightarrow & D_4 & \rightarrow & E_1 \\
 & & & & & & & & & \\
\pi_j^{(4)} = & & & & & & & D_4 & \rightarrow & E_1
\end{array}$$

Figure 1: Example of computation of the metric $\mathbb{S}$ for one EV ($A_1$ is the departure point, $B_1$, $C_1$, and $D_1$ are the initially planned charging stations, and $E_1$ is the arrival point). Each red arrow represents a planned charging station that changed after a replanning. Each replanning uses the next station to be reached (according to the previous plan) as a starting position. If a vehicle has still not departed from the starting position of its previous plan, the starting position is kept the same for the next replanning. That explains why $\pi_j^{(1)}$ and $\pi_j^{(2)}$ both starts at $B_1$: the $j^{\text{th}}$ EV was still waiting or charging at $B_1$ during the second replanning.

The new term $\delta(\pi_j^{(i)})$ is defined as:

$$\delta(\pi_j^{(i)}) = \begin{cases} \phi_j \sum_{k=1}^{k_j^{(i)}} r_j^k \left[ \pi_{j,k}^{(i)} \neq \pi_{j,k}^{(i-1)} \right] & \text{if } i > 0, \\ 0 & \text{otherwise,} \end{cases}$$

where $[P]$ is the Iverson bracket, defined as:

$$[P] = \begin{cases} 1 & \text{if } P \text{ is true,} \\ 0 & \text{otherwise,} \end{cases}$$

$k_j^{(i)}$ is the number of stations in $\pi_j^{(i)}$ — the plan of the $i^{\text{th}}$ vehicle during the $j^{\text{th}}$ replanning — and $(\phi_i, r_i)$ are parameters controlling respectively (1) the importance that the driver of the $i^{\text{th}}$ EV gives to the plan stability, and (2) the geometric decay of the penalty over time for that EV (e.g., we might want to penalize more a change to the next planned station than we do for a change to a future replanned station).

Assuming there were $m$ replannings in total, we propose to compare the stability of plans obtained with the baseline CEVPP formulation and with our proposed extension using the following metric:

$$\mathbb{S}(\pi^{(0)}, \pi^{(1)}, \dots, \pi^{(m)}) = \sum_{i=1}^{m} \frac{1}{n_i} \sum_{j=1}^{n_i} \sum_{k=1}^{k_j^{(i)}} \left[ \pi_{j,k}^{(i)} \neq \pi_{j,k}^{(i-1)} \right].$$

The metric $\mathbb{S}$ is the average of the number of changes of the charging stations planned for each EV. A visual representation of that metric for one EV is shown in Figure 1.

| Test characteristics | | Baseline | | Stability-aware extension | | Change | |
|---|---|---|---|---|---|---|---|
| **Network** | **#EVs** | $\mathbf{Z}(\pi)$ (min) | $\mathbb{S}$ (# changes) | $\mathbf{Z}(\pi)$ (min) | $\mathbb{S}$ (# changes) | $\mathbf{Z}(\pi)$ (min) | $\mathbb{S}$ (%) |
| Québec$_{347}$ | 8 | 1.9 | 0.1 | 1.9 | 0.1 | 0.0 | 0.00 |
| Québec$_{347}$ | 16 | 3.1 | 1.3 | 4.5 | 0.7 | 1.4 | -46.15 |
| Québec$_{347}$ | 32 | 10.6 | 6.2 | 10.9 | 1.9 | 0.3 | -69.35 |
| Québec$_{347}$ | 64 | 28.3 | 31.3 | 31.3 | 19.0 | 3.0 | -39.30 |
| Québec$_{347}$ | 128 | 27.9 | 72.7 | 37.7 | 34.5 | 9.8 | -52.54 |
| Québec$_{1816}$ | 8 | 0.5 | 0.9 | 0.5 | 0.8 | 0.0 | -11.11 |
| Québec$_{1816}$ | 16 | 0.7 | 2.4 | 2.0 | 1.1 | 1.3 | -54.17 |
| Québec$_{1816}$ | 32 | 6.2 | 3.3 | 8.2 | 2.6 | 2.0 | -21.21 |
| Québec$_{1816}$ | 64 | 11.2 | 34.4 | 19.2 | 16.5 | 8.0 | -52.03 |
| Québec$_{1816}$ | 128 | 73.0 | 230.5 | 113.0 | 116.5 | 40.0 | -49.46 |

Table 1: Comparison of the baseline and stability-aware CEVPP planners based on pcEVP in terms of $\boldsymbol{Z}$: penalty, in minutes, of the solution compared to the theoretical best case, and $\mathbb{S}$: metric of plan stability, on the Québec$_{347}$ and Québec$_{1816}$ road networks. Each row reports the average of the results over 10 CEVPP requests.

## 4 Experiments

In this section, we conduct an empirical evaluation to compare the baseline CEVPP (which uses the $Z$ objective function) and our proposed extension (which uses the $\bar{Z}$ objective function). We measure and compare two metrics: (1) the penalty $Z(\pi)$ of the executed plans, and (2) the metric $\mathbb{S}$ of the plan stability defined above. In our experiments, we fixed the parameters $\phi_i$ to $15$ and $r_i$ to $1.0$ for all EV $i$.

The pcTVI algorithm and the proposed extension were implemented in C++ and compiled using the GNU g++ compiler (version 13.2). All our experiments were performed on a PC computer equipped with a 4.2 GHz Intel Core i5-7600K CPU and 32 GB of RAM.

All tests were conducted on a real road network and real charging stations using the pcEVP planner. We don't report here the running times, as the extension we propose has a negligible impact on the running time of the pcEVP planner.

Since the proposed extension of the CEVPP problem keeps the next planned station of each EV fixed, only EV plans requiring more than one charging station can change after a replanning. Therefore, in our empirical evaluation, we considered a vast road network covering the territory of the Québec Province (Canada), where the journeys between certain pairs of cities can be very long (thus requiring several recharges) and where the network of charging stations is relatively well developed. The road network data (i.e., the nodes and the road segments) were taken from the OpenStreetMap project (Weber and Haklay 2008).

The stations considered in the tests come from a public network of EV charging stations called the *Electric Circuit* (Hydro-Québec 2023). We used two different sets of stations in our evaluation, with respectively $347$ and $1816$ stations. In the implementation, without loss of generality, each charging station had the same power output and all EVs were charging at a constant rate of $9$ km/min.

To assess the performance of the proposed algorithms, we generated random sets of EV requests, ranging from 8 to 128 EVs per set. For each set, we randomly sampled two stations at least 200 km apart. We then sampled from a 100 km cluster around these stations the departure $\alpha$ and destination $\omega$ nodes to simulate multiple EVs journeying along similar paths. The range of each vehicle was sampled uniformly between $100$ and $550$ km. Finally, the departure time of each vehicle was sampled uniformly between $0$ and $4$ hours.

Table 1 shows the results of our empirical evaluation. The first two columns present the characteristics of the test (the name of the network, either Québec$_{347}$ or Québec$_{1816}$, and the number of EVs in the fleet). The next four columns present the penalty $Z$ and the evaluation metric $\mathbb{S}$ for the baseline CEVPP formulation and the proposed extension. Finally, the last two columns present respectively for the penalty $Z$ and the metric $\mathbb{S}$ the variation between the baseline CEVPP formulation and the proposed extension. Each test (i.e., each row in the table) consisted of running $10$ CEVPP instances. We report in the table the averages obtained over $10$ experiments. We also present these results graphically in Figure 2 and Figure 3, representing respectively the penalty $Z$ and the metric $\mathbb{S}$ for the baseline CEVPP formulation and the proposed extension on both networks.

The results we can observe in Table 1 and in Figures 2 and 3 suggest that the proposed extension of the CEVPP problem considering the plan stability can significantly reduce the number of changes in the originally planned charging stations, thereby increasing the plan stability. On average over all tests, the proposed method reduced the number of changes by $39.53\%$ compared to the baseline CEVPP. This is achieved without significantly increasing the penalty of the executed paths compared to the baseline CEVPP formulation. On average, the penalty increased by only $0.13$ minutes per EV compared to the baseline CEVPP. The results suggest that the percentage of reduction of the number of changes in the planned charging stations could have been even higher (by increasing the value of the parameter $\phi_i$) while keeping a relatively low penalty of the executed paths.

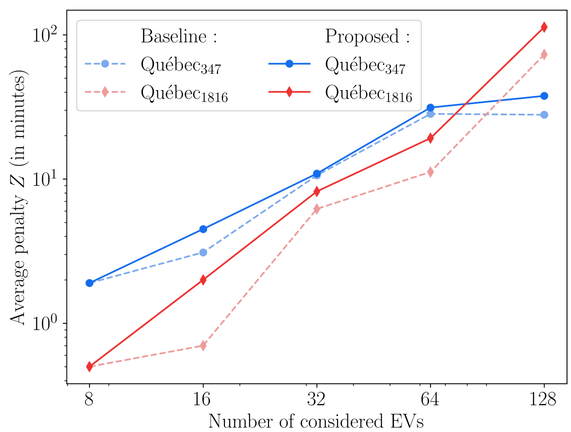


Figure 2: Average (over 10 experiments) penalty $Z$ as a function of the number of EVs on the road for the baseline algorithm and the proposed extension for the two considered road networks. Both axes use a logarithmic scale.

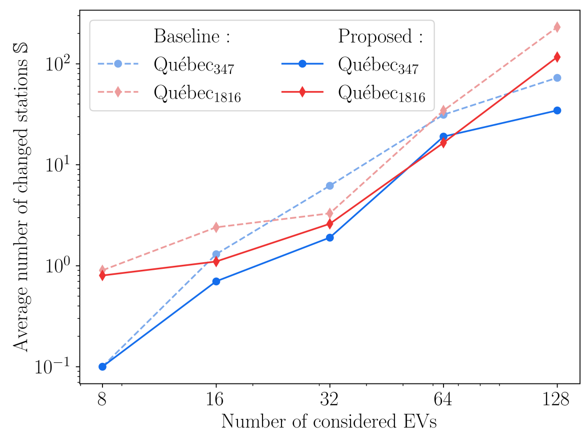


Figure 3: Average (over 10 experiments) metric $\mathbb{S}$ as a function of the number of EVs on the road for the baseline algorithm and the proposed extension for the two considered road networks. Both axes use a logarithmic scale.

## 5 Conclusion

In this paper, we proposed an extension of the Cooperative Electric Vehicles Planning Problem (CEVPP) that takes into account the predictability of the plans and considers plan stability in its objective function. We showed that our approach can significantly reduce the variability of the plans, while keeping low the global plan execution time. The proposed extension can be parameterized dynamically to adapt to the preferences of the EV drivers.

In our evaluation, we fixed the parameter $\phi_i$ to 15 for all EVs, thus controlling the importance given to the plan stability. Future work will focus on a more thorough empirical evaluation, where we will vary the parameter $\phi_i$ to assess its impact on the plan stability and the penalty of the executed paths. Therefore, our future investigation will address the problem of trade-off between the plan execution time and the plan stability. Moreover, we plan to compare the proposed extension with existing approaches used to increase the plan stability in other multi-agent planning problems.

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