# A framework for electric vehicle charging strategy optimization tested for travel demand generated by an activity-based model

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*Abstract*— this paper presents the cost optimization model which plans a charging strategy for an electric vehicle. In case of time dependent electric prices an intelligent planner is required which plans the charging strategy only at cheaper moments and places to keep the vehicle charged enough to complete its scheduled travels. This model estimates the required charging energy to travel by the electric vehicle. Then using the time dependent electric prices and available power at each period of the time suggests a charging pattern for the electric vehicle which ensures the cheapest charging cost and fulfills the constraints of battery state of the charge. According to the current market share of electric vehicles, a fraction of daily agendas created by the large scale activity-based model are used to test the proposed framework. A central power tracker is introduced which keeps track of available and required power at each period of the day. It also manages the charging requests from electric vehicles. Moreover, an experiment has been set up, it makes use of wind and solar energy production data. Price signal is derived from available power as an indicator of relative cost.

*Keywords—electric vehicle; charging optimization; renewable energy; electric demand*

## I. DEFINITIONS OF TERMS USED IN THE TEXTS

**BEV:** Battery only electric vehicle

**DCD:** Deepest charging depletion

**SOC:** State of charge of the battery

**Optimization Token:** a permission message to the vehicle to start its charging optimization process

**Active Communication window:** the group of consumers who are allowed to perform their local optimization in parallel.

**Slot Blocked Globally:** a time slot where all of the power is already booked.

**Slot Blocked Locally:** a time slot where power is available but it is blocked because vehicle is traveling entirely over the overlapped period of the slot.

**Saturated slot:** a time slot where more energy cannot be charged by the vehicle because already charging planned for complete period of the slot, or more charging at the slot will cause the battery overfull due to already booked energy in successive slots.

**INITSOC:** SOC level of the battery at the start of the schedule.

## II. INTRODUCTION

A rise in market share value of electric vehicles is forecast for the coming years. There are still many challenges (cost, charging opportunities, charging time, safety and reliability, range limitations etc.) to meet the expected penetration of electric vehicles in the market [3]. Renewable power can be used for green transport to reduce the $CO_2$ emission. In Belgium, there is excess amount of wind and solar capacity installed already [4]. Figure 1 shows that the percentage of renewable (solar and wind) power of the overall power production in Belgium on average varies between 3 to 20 percent during summer and between 6 to 12 percent during winter time. Electricity production from renewable resources is highly variable. Batteries in electric vehicle can store the excess amount of power to use it later when less amount of power is available. Hence electric vehicle can be useful to mitigate the problem of unpredictability of wind and solar power. Variable production of power, on the other hand, causes variable electric prices with respect to the demand. To charge the electric vehicle only during the periods when the renewable energy is available in excess and the energy price is lower as well as to keep the vehicle charged enough to execute all the scheduled trips is a difficult task.

During the recent years a lot of work done for optimization of charging strategy for the electric vehicle. Most of the suggested research was focused on control charging of the vehicles by the grid operator [7-10]. Grid operator side charging optimization is suggested to balance the energy demand from electric vehicles at peak hours. Controlled charging strategy can help and improve the grid efficiency and reduce the power losses [7]. Electric vehicles can be good contribution for renewable power usage with load management using grid communication [8]. A smart control strategy based on quadratic programming is used to minimize the peak load and flatten the overall load profile [9]. In [10] a comparison between linear and quadratic approximation of the EV batteries to plan the charging has been presented. Reference [11] uses the time of use price of electricity in regulated market to control the electric vehicle charging load. A flexible charging scheme of electric vehicle can create the optimization problem for different stake holders like wind producers, and grid operators [12]. It is not realistic that each

traveler will declare his/her available time at each charging location due to privacy reasons. Hence, an optimization process is needed which can be used within the car to optimize it charging strategy.

In this paper an electric vehicle charging planner (EVCP) is presented which tracks the booked and available renewable energy and on the other hand optimizes the charging strategy for the vehicle. After the traveler feeds his/her traveling plan for next planning horizon to the car, the car intelligence requests the available power and energy price from the central power tracker, optimizes the charging strategy for the vehicle and updates the central power tracker about the booked energy for each charging event. Central power tracker takes the forecast renewable energy production information and manages the booked and available energy at each charging slot. EVCP currently based on one-day-ahead planning. The model uses the day ahead information about forecast renewable power production and takes the schedule of the complete day of the vehicle owner. The schedules (agendas) for each inhabitant of Flanders (Belgium) are generated using the FEATHERS activity-based model described in Bellemans et al. [1].
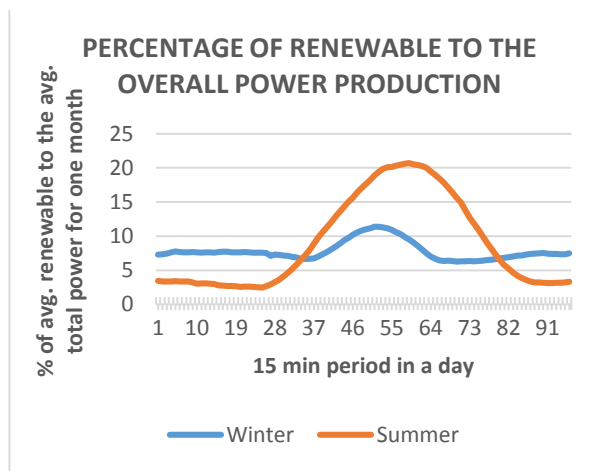


Figure 1. Percentage of average renewable Power to the average complete power produced in each 15 min of the Day for one month

### III. FRAMEWORK CONCEPTUAL OVERVIEW:

The conceptual overview of EVCP framework is shown in figure 2. EVCP has two main parts: 1) central power tracker 2) car intelligence. Central power tracker (CPT) provides the central role to manage the energy utilization. It takes renewable power production information from power supplier and keeps track of the available and booked power at each time slot. It also takes information about the price from the power supplier. Car intelligence is the user side part of the framework which carries out the optimization process for the vehicle. Once the owner feeds his schedule to the car for the next planning period, car intelligence starts the optimization process. It first sends the request to central power tracker to get the information about available power and price of the energy at each charging slot. This request is received by the CPT. Then the CPT sends the data about available power and price for each time slot back to the car intelligence. Car intelligence uses the information about travel requirements,

battery capacity, available (not already booked) power, electricity price, and availability of charger to optimize the charging strategy for the vehicle for next planning period. A detailed description of charging strategy optimization process is given in section IV. After optimization, the car intelligence sends a message back to CPT containing the information about all charging events. This message contains the information about charging start time, duration, and energy drawn from grid for all charging events in 24 hours planning period. After receiving the booking message, CPT updates its track of booked power and available power for each charging slot.

All the requests sent from vehicles are stored in the request queue where requests are served on first come first served basis. To make the communication between vehicles and CPT in parallel, a special mechanism has been designed. That means a number of cars (active communication window size) are given the optimization token at same time. Active window communication size can vary from 1 to the degree of parallelism (DOP). The mechanism to find the DOP is described below. All requests which are stored later in the queue are kept on hold until the booking reply is received from the batch of vehicles which were given the optimization token in parallel. In the real context timeout mechanism is to be provided since some cars can fail to send a response within a reasonable period. Before passing the optimization token to the next batch, CPT reevaluates the DOP to update the active communication window size.
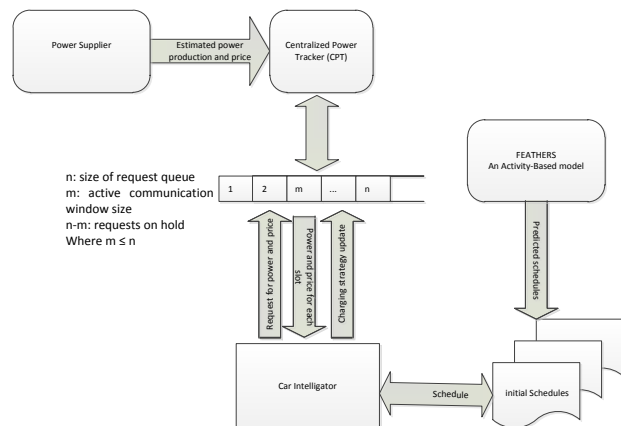


Figure 2 Conceptual overview of EVCP framework

The electric vehicle will use possibly different charging power at different parking locations (i.e. power of the charger used at home and at work). In this framework it is assumed that each car already knows for each locations (i.e. home, work) whether charger will be available to charge or not. In this experiment it is assumed that each car can charge at its home and work locations. It is also assumed that if charger is available at any location, car knows its power rating to charge the energy. Then car finds the location at which it can charge at fastest rate. Then it marks the power of the charger at the found location as $Ch_{\max}$. When the car sends the request for optimization token, it also declare the $Ch_{\max}$ to the CPT. Then CPT calculates the maximum $Ch_{\max}$ ($chPower_{max}$) out of all received request. Suppose that $C$ requests are received,

hence, $Ch_{\max}{}^c$ is already received for each request. Then $chSwitch_{max}$ will be calculated as following:

$$chSwitch_{max} = \max_{1 \leq c \leq C} Ch_{\max}{}^c$$

CPT marks the time slot as unavailable if all of the power is booked for the particular time slot. While calculating the degree of parallelism, CPT finds the time slot with minimum available power out of all available time slots. Using information about time slot with minimum available power and maximum charger power, CPT calculates the active communication window size using following equation:

$$DOP = \frac{availPower_{min}(t)}{chSwitch_{max}}$$

## IV. CHARGING STRATEGY OPTIMIZATION PROCESS

After receiving the traveling plan, the available power and energy price, car intelligence starts its charging strategy optimization. Detailed algorithm is described below.

Suppose that car $C$ receives its traveling schedule $S$. First it reads the available energy $E$ and price $Prc$ for each period $p$ of the day $D$. It is assumed that Car has its battery SOC at some $INITSOC$ level at start of the day. For all trips $T$ in the schedule $S$ where car $C$ is used as transport mode, the optimizer ensures that car battery should have enough energy charged so that it does not go below to the minimum level. DCD level of the battery is used as minimum threshold for battery SOC for all trips except of the last trip where INITSOC is used as threshold. In case of battery SOC goes below to the minimum level after a particular trip, the cheapest time slot is found between two time periods $t_0$ and $t_1$, where $t_1$ is the first period of the trip and $t_0$ is the last period when battery was full. In case of no battery full event found, starting period of the schedule is used as $t_0$. Available time slots are ordered using increasing cost. The list of available time slots is scanned and a slot is selected for the car if all following conditions are fulfilled:

i. The requested amount of power is available at the time slot.
ii. The vehicle is not traveling completely during the period associated with the time slot. It should have some parking moments during the period.
iii. The time slot is not yet booked for the vehicle.

If any slot is found, car need to determine at which rate energy will be charged at this slot. It depends upon the power of the charger that will be used for charging at the found time slot. So, the car first determines at which location it will be parked at the found time slot (i.e at home or at work).

If any slot is found, then it determines the location of the car during the time slot period: location determines the power of available charger that will be used to charge the energy at the found slot. Then, it determines the vehicle presence time at this location overlapped with period of found slot. Using this presence time and charger power it calculates the maximum energy $E_{max}$ which can be charged at this particular slot. Then it calculates the effective energy that is planned to charge at this slot by taking the minimum of required energy to meet minimum energy level constraint,

available energy from the grid at this slot, maximum energy that can be charged during this slot, and the amount of the energy that can be charged before the battery gets full during already planned charging in successive slots. This effective energy is added to the battery SOC. If no usable slot is found, then, this schedule is marked as "soft infeasible" if battery SOC was above than DCD level and it was the last trip of the schedule for which violation occurred otherwise it is marked as "hard infeasible". If this optimization process successfully iterates over all trips to keep the battery SOC above minimum level at each point in time, this schedule is marked as "feasible". In case of feasible or soft infeasible schedules, information about charging events booking information is sent back to CPT.

Algorithm 1 shows the main components of the optimizer used by the car logic. Lines 1-4 perform general initialization with data received from CPT. Lines 5-33 determine the optimal set of charging slots. Lines 34-41 specify the required minimum SOC at the end of trip $T$ before the next trip is processed.

Algorithm 1. Algorithm for Electric Vehicle to optimize the charging strategy

1.  *for $p \in D$ do*
2.      *$E[p] \leftarrow read()$*
3.      *$Prc[p] \leftarrow read()$*
4.  *end for*
5.  *$C.SOC[0] = INITSOC$*
6.  *for all $T \in S.TripSet()$ do*
7.      *$t_1 \leftarrow T.startTime()$*
8.      *$minLevel \leftarrow minReqdBatteryLevel()$*
9.      *while $C.SOCatEndOfTrip(T) < minLevel$ do*
10.         *$t_0 \leftarrow lastTsFullBattPred(T)$*
11.         *$cs \leftarrow cheapestUsableSlotIn(t_0, t_1)$*
12.         *if $cs \neq null$ then*
13.             *$S.markAsPlanned(cs)$*
14.             *$chrgPwr \leftarrow S.location(cs).power()$*
15.             *$Ereq \leftarrow energyRequired(cs)$*
16.             *$\Delta t \leftarrow durationAt(s.location(cs))$*
17.             *$E_{eff}, \leftarrow min(E_{req}, E[cs], E_{max}\,(chrgPwr, \Delta t), E_{SOC}\,(S.SOC[cs]))$*
18.             *$C.SOC[cs + 1] \leftarrow C.SOC[cs] + E_{eff}$*
19.             *$E[cs] \leftarrow E[cs] - E_{eff}$*
20.             *$cs.markAsScheduled(cs)$*
21.         *else*
22.             *Goto: END*
23.         *end if*
24.         *$minLevel \leftarrow minReqdBatteryLevel()$*
25.     *end while*
26. *end for*
27.         *S.mark("feasible")*
28. *END:*
29.     *if $s.index(T) = Last$ AND $C.DCD < C.SOCatEndOfTrip(T) < INITSOC$*
30.             *S.mark("soft infeasible")*
31.     *else*

```
32.          S.mark("hard infeasible")
33.      end if
34.  Function minReqdBatteryLevel()
35.      If S.index(T) = LastTrip
36.          minLevel ← INITSOC
37.      else
38.          minLevel ← C.DCD
39.      end if
40.      return minLevel
41.  end Function
```

## V. ACTIVITY BASED MODEL TO PREDICT THE DAILY SCHEDULES

The present framework assumes that all EV owners know their traveling agenda prior to start the charging strategy optimization process. The FEATHERS Activity-based modeling is used which predicts the travel agendas for the complete population of the study area. FEATHERS is a large scaled activity-based modeling framework which predicts the daily agendas for complete population of Flanders (Belgium) [1]. FEATHERS predicts the agenda containing the details for each trip for the given day for each individual. The daily agenda for each individual starts after last home arrival from previous day and ends at last trip to the home for the current day. Each tuple of the predicted trip contains information about origin, destination, start time, duration, travel mode, and type of the activity. Type of the activity can be home, work, leisure, shopping, pick/drop, or social visit. EV specific travel schedules are distinguished from regular car transportation trips as they cover a predefined maximal distance between charging opportunities. The simulations to test the proposed framework, use the Feathers predicted EV schedules as input data. Feathers predictions have been used in [2] to calculate the electric power demand generated by EV charging for each zone in Flanders as a function of time under several charging behavior scenarios. EV market share and charging opportunity (at home, at work) assumptions.

## VI. TEST SIMULATIONS OF THE FRAMEWORK

According to the current market share of electric vehicles [6], a fraction of daily agendas created by the large scaled activity-based model are used to test the proposed framework. From selected set of schedules, all schedules which contain any trip covering more than predefined maximum distance between two consecutive charging opportunities are dropped. Maximum predefined distance depends upon the battery capacity of the EV. Car category is selected using the probability for each category (small, medium and large) given in table below. Battery capacity, battery range and energy consumption lower and higher limits are selected specific to the selected car category. Car specific energy consumption is selected is sampled from a uniform distribution between lower and high consumption limits. In this test suite, charging is only kept possible at home and work locations using 3.3 kW or 7.2 kW power chargers. Out of two possible charging switches one charger is selected at each work and home

location for each car using the probability values as described below. INITSOC is used 30% of the battery capacity for all cars. A detailed overview of all values of these characteristics is given in table 1.

Table 1. Correspondence between EV and ICEV for categories specified in Belgian Government statistics

| | Vehicle categories | | |
|---|---|---|---|
| Equivalent engine cylinder volume [cc] (ICEV category) | V < 1400 | 1400 ≤ V ≤ 2000 | 2000 < V |
| Market share (from Belgian government statistics) | 0.496 | 0.364 | 0.140 |
| EV category | small | Medium | Large |
| Battery capacity (kWh) | 10 | 20 | 35 |
| Range (km) | 100 | 130 | 180 |
| Energy consumption (kWh/km) : lower limit | 0.090 | 0.138 | 0.175 |
| Energy consumption (kWh/km) : upper limit | 0.110 | 0.169 | 0.214 |
| Charger type at home : Prob(3.3[kW]) | 0.8 | 0.4 | 0.1 |
| Charger type at home : Prob (7.2[kW]) | 0.2 | 0.6 | 0.9 |
| Charger type at work : Prob (3.3[kW]) | 0.1 | 0.1 | 0.1 |
| Charger type at work : Prob (7.2[kW]) | 0.9 | 0.9 | 0.9 |

FEATHERS creates **2395514** schedules, out of which **1057147** schedules contain at least one car trip. Using the market share for BEV of 10 % of the total vehicle fleet, we sample **105801** schedules from the complete set using a uniform distribution. From this first sample we remove the schedules that cannot be driven using a BEV due to limited vehicle range and lack of intermediate charging opportunities. Hence, only **90569** schedules are left which are used to test the presented framework.

To test the presented framework, data about available renewable power from Elia, Belgium's electricity transmission system operator [5] is used. Using the market share value for BEV of 10% of the total vehicle fleet, total electric demand for one day to charge the EVs in Flanders is **1,815,534 kWh** while total available renewable power for one day is **20,770,400 kWh**. Hence to make the test simulation interesting available power is downscaled 10 times at each 15 min period. Price signal is derived from available power as an indicator of relative cost using the following equation. This price is not absolute price of the energy but it is only a relative price signal.

$$Price_t = \frac{1}{Power_t} * 1000$$

Available power and price used for the simulation are shown in figure 3.
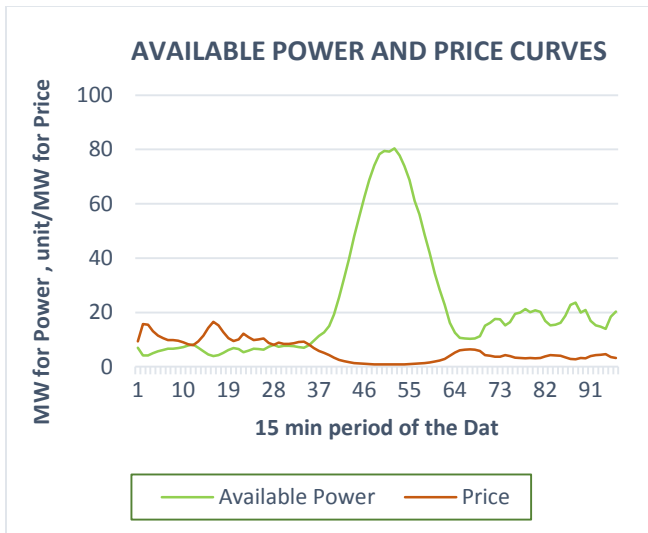
Figure 3. Available power and price of energy at each 15 min period of the day

## VII. RESULTS

The electric vehicle used for each schedule can start the optimization process till the last moment before executing the schedule. This optimization process depending upon the energy demand for travel and available power, devises the charging strategy for the car. The process creates the charging plan for the EV as a sequence of charging events. Each charging event contains information about start and end of charging event, amount of energy charged, place of charging and power at which energy is charged. Optimization process marks the resulting strategy as feasible, soft infeasible or hard infeasible. Information about charging events is sent back to CPT in case of feasible or soft infeasible strategy, while a negative signal is sent in case of hard infeasible strategy. Examples of feasible and hard infeasible charging strategies are shown in form of battery SOC timeline in figure 4 and figure 5 respectively. Legends used in SOC timeline figure are explained in table 2.

**Feasible strategy:** if battery SOC level at the end of the schedule and at the start of the schedule are equal.

**Soft infeasible:** if initial battery SOC level cannot be prevailed but the SOC at any other time does not violate minimum level requirement.

**Hard infeasible:** if initial battery SOC level cannot be prevailed and the minimum DCD level requirement is violated at least once.

Table 2. Legends used for charging strategy timeline

| | | | |
|---|---|---|---|
| 🟩 | Parking at the location where charging switch is available. | 🟩 | Parking at the location where charging switch is unavailable. |
| 🟥 | Traveling with Car | 🟨 | Traveling without Car |
| 🟫 | Slot blocked globally: All power is booked already. | 🟧 | Slot blocked locally: more charging impossible. |
| 🟦 | Saturated slot: Planned to charge for complete time of the slot. | 🟦 | Planned to charge energy at the slot. |
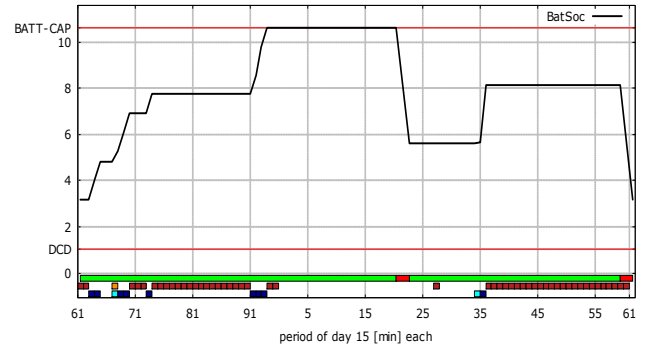


Figure 4 Example of feasible charging strategy
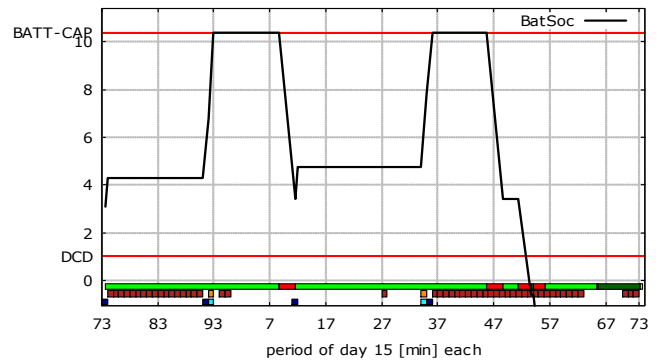


Figure 5 Example of hard infeasible charging strategy

In this test simulation, optimization process is carried out for *90569* EV. Out of them, *85872* BEV succeeded as feasible strategy, *4001* as soft infeasible, and *379* as hard infeasible strategies. The optimization process took *0.63* millisecond for each car on average.

In figure 6 a comparison is presented between available and consumed power for each 15 min period of the day. Power is booked completely during the relatively cheaper moments of the day.
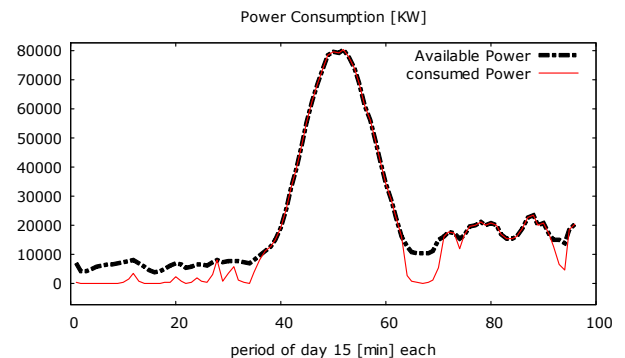


Figure 6. Comparison between consumed and available power

## VIII. CONCLUSION

In this paper a framework is designed which has two parts; 1-central power tracker 2- Car intelligence. Central power tracker provides tracking of available and consumed power

while car intelligence optimizes the charging plan for car to charge only at cheapest moment with fulfillment of constraints of battery SOC and energy demand for travel. It also tries to keep the battery charged equal to the initial battery SOC level. It, then, marks the charging strategy as feasible, soft infeasible and hard infeasible. It is first kind of detailed charging strategy optimization process with charging opportunity at more than one locations and is tested for large scaled study area.

## IX. FUTURE WORK

Current presented work is focused about minimizing the charging cost. Customers do not modify their agenda. The next step is to find out whether a customer can charge at even lower cost by adapting his/her agenda to the time dependent energy cost. Hence, a value of time function is required which can convert the shift in time to the money. Where converted money could be used as comparator to decide what is cheaper: shift charging events in time and space or pay more for the required energy.

In current work, only time dependent energy cost is used to test the framework. An extension in current work is required which incorporates the temporal-spatial cost of energy.

In current model it is assumed that life is periodic. Everyone have same agenda for each day and available power is also same for each day. All those persons who arrive home earlier than others, will always get the opportunity when all of the cheaper power is available. In the extended model, customers will mutually influence each other's travel behavior via cost to charge scarce electric energy.

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