Logistics system planning for battery-powered electric vehicle charging station networks

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Abstract. This work proposes a promising scenario of large-scale deployment of battery-powered electric vehicle charging station networks that attempts to address three important issues toward a sustainable energy landscape in the near future: (1) Suppressed grid integration of variable renewable generations such as wind; (2) Low profitability of battery energy storage systems due to limited applications; and (3) Conflicts between the current power infrastructure and the installation of charging stations to meet the growing needs of electrical transportation. More specifically, we design a system in which electric trucks deliver large-volume batteries to electric vehicle charging stations. This facilitates the planning and operation of electric vehicle charging station networks without constraints from the grid. In regions where there are abundant renewable energy sources and the road networks do not suffer from frequent congestion, this could be a viable solution. Using the city of Corpus Christi, Texas (USA) and the nearby Chapman Ranch wind farm as a test case, we formulate the design problem based on the logistics system models and obtain the optimal sizes of charging station batteries and number of electric trucks to minimize cost. The obtained results can help potential stakeholders make business decisions or policy recommendations.

1. Introduction

Electric vehicles (EVs) play a significant role in making the transportation system more sustainable by achieving substantial reductions in greenhouse gas emissions. At present, the power grid is not severely affected by EV deployment due to their low penetration to the market. However, the target set by the International Energy Agency (IEA) [1] for having over 125 million EVs deployed on the road by 2030 would pose great challenges to the grid and may create large spikes in demand [2]. To maximize the utilization of variable renewable resources such as wind and solar while increasing the profitability of battery energy storage systems (BESS) that stores this excess power, a new concept has emerged from our previous work in [3] and [4] which envisions a transition from a conventional, stationary BESS to a mobilizable BESS. More specifically, we design a system in which electric trucks transport the batteries between BESS and electric vehicle charging stations (EVCSs). This will facilitate the planning and operation of EVCS networks without constraints from the grid. This paper develops the above idea by proposing a promising scenario of large-scale deployment of battery-powered EVCS networks that holds promises to address three important issues toward a sustainable energy landscape in the near future: (1) Suppressed grid integration of variable renewable generations such as wind [5]; (2) Low profitability of BESS due to limited applications [6]; and (3)
Conflicts between the current power infrastructure and the installation of charging stations to meet the growing needs of electrical transportation [7]. In many areas in the United States (Texas for example) where there are abundant renewable energy sources and the road networks do not suffer from frequent congestion, this could be a viable solution.

Logistics network and management are vital elements for the planning and operation of the proposed EVCS networks. Logistics system planning for the EVCSs will facilitate and accelerate the market penetration of EVs and result in operational cost reductions [8]. In this work, using the city of Corpus Christi, Texas and the nearby Chapman Ranch wind farm as test case, an optimization problem for the design of the aforementioned logistics system is formulated and solved to obtain the optimal number of batteries required at each EVCS as well as the number of electric trucks that leads to minimum the operational costs. It is worthwhile to mention that the efficient logistics system for the mobilizable BESS can also be used during disaster relief [9] or as backup power sources for critical facilities.

However, in this work, our focus is on the EVCS network that is the sole consumer.

The organisation of the rest of paper is as follows: In Section 2, the problem statement including the objective function, constraints, data, and solution methods are presented. In Section 3, the numerical results are obtained and discussed. Conclusions and suggestions for future work can be found in Section 4.

2. Approach

The problem setting has been established in our recent work [3] where the capacity of a hypothetical BESS accompanying the Chapman Ranch wind farm was determined via historical data analysis. Following that, in [4], the locations and numbers of charging facilities of the EVCS networks (27 stations) in Corpus Christi were optimized assuming the demand of around 10,000 EVs in the city. Fig. 1 marks the locations of the BESS and the EVCSs on a map. The previous effort clarifies the supply and demand ends of the whole system. This work will be devoted to the design of logistics system as the link between supply and demand, in which the number of electric trucks and the number of batteries at each EVCS are the two most important variables.

![Figure 1. The locations of the BESS at the Chapman Ranch and the 27 EVCSs in Corpus Christi city, Texas (USA).](image)

2.1. Logistics system configuration

The typical logistics configuration, as illustrated in Fig. 2(a), includes four main components: the plant, storages (or wholesalers/distribution centres), retailers, and the end customers [10]. The proposed BESS logistics system configuration in Fig. 2(b) combines the plant and the storage at the same spot and excludes the retailer role to save portions of the costs to the customers. This network is modelled as a one-to-many distribution system. The objective of this research is to optimize key parameters for
the best configurations using logistics systems analysis methods [11]. Here we use a simulation-based method for optimization.

![Diagram of logistics configuration](image)

**Figure 2.** (a) The typical logistics configuration. (b) The proposed BESS logistics configuration.

### 2.2. Main conditions and constraints for the logistics system planning

Consider the case of mobilizable batteries. Each battery is assumed to have a capacity of 5 MWh, and to be shipped by electric semi-trucks (EST) to the EVCSs when required. The requirement for each shipment is estimated by the daily demand of EVCSs individually as detailed in [4]. The distance and time required to be travelled between the BESS and each EVCS is obtained using Google maps, the exact locations of the BESS at the Chapman Ranch and the 27 EVCSs in Corpus Christi city are illustrated in Fig. 1. Based on the cost of each battery and EST, our algorithm is run to optimize the number of batteries required at each EVCS and the number of ESTs for this logistics scenario, so that the overall cost is minimized. The initial number of batteries for the logistics management at each EVCS is estimated by half of a full day demand (batteries) of that station, for instance, EVCS#1 requires 22.848 MWh/day, which is about 5 batteries (5 MWh each), so the initial number of batteries for EVCS#1 is 3 batteries.

On the other hand, the initial number of ESTs for the logistics system is selected based on the travel time and distance to each EVCS from the BESS. The minimum number of ESTs can be found as the maximum overlaps between the time intervals for the ESTs movements between the BESS and the EVCSs as shown as an example in Fig. 3. To identify the overlaps, for each EVCS, first the time \( t_{\text{req}}(i) \) when a battery is needed to be shipped has to be found based on the number of batteries \( N_B(i) \), capacity of each battery \( B_{\text{cap}} = 5 \text{ MWh} \) and the discharge rate \( d_r \) of that station as formulated in Eq. (1).

Then, with estimated transportation time from BESS to the station \( t_T(1) \), the start and return trip times of each ETS are obtained from Eqs. (2) and (3).

\[
\begin{align*}
  t_{\text{req}}(i) &= \frac{N_B(i) \times B_{\text{cap}}}{d_r(i)} \\
  t_s(i) &= t_{\text{req}}(i) - t_T(i) \\
  t_r(i) &= t_{\text{req}}(i) + t_T(i)
\end{align*}
\]
Figure 3. Illustration of time windows of ETSs movements. For each EVCS, the window is centred at the time when its state of charge is expected to fall below the minimum level and extend to the left and right by the travel time from and to the BESS.

The maximum number of overlaps between the resulting time intervals \([t_s(i), t_f(i)]\) can be found which represents the number of ESTs \(N_{EST}\) that need to operate at the same time. Each EVCS should have at least one battery as a minimum condition, and not to exceed the number of batteries that is equivalent to a full day demand \(N_{B,FD}(i)\) as a maximum condition which is represented in Eq. (4).

\[ 1 < N_B(i) \leq N_{B,FD}(i) \] (4)

2.3. Objective function

The objective of the optimization problem is to minimize the annualized cost of the proposed logistics system. The annualized investment cost \((C^I)\) is a combination of the EST cost \((C^{EST})\), the batteries cost \((C^B)\), as well as the annual operation and maintenance cost \((C^{O&M})\) of the system. The objective function is expressed as:

\[ \min \ Cost = C^I + C^{O&M} \] (5)

where the annualized investment cost is represented by:

\[ C^I = \alpha C^{EST} + \beta C^B + \delta C^{plant} \] (6)

where \(\alpha, \beta\) and \(\delta\) are auxiliary variables associated with the EST, batteries and plant respectively to annualize the capital investment. They can be calculated from:

\[ \alpha, \beta, \delta = \frac{d(1 + d)^{EST,B,plant}}{(1 + d)^{EST,B,plant} - 1} \] (7)

The total costs of both ESTs and batteries are shown in Eqs. (8) and (9) where \(\mu\) is the price of each EST which is according to [12] and [13] in a range of $150k – $200k. And \(\tau\) is the price of each 5 MWh battery, which, according to [14], is estimated as $100 per kWh. Since this research targets the future, it is still uncertain what these costs will be. In view of this, in our work, different values will be used for comparison.

\[ C^{EST} = \mu N_{EST} \] (8)

\[ C^B = \tau N_B \] (9)

The annual O&M cost of the logistics system is:

\[ C^{O&M} = \sigma D_{tot} + \varphi C^{EST} + \omega C^B + \psi N_{EST} \] (10)
where the cost for each trip ($\sigma$) is estimated by around $0.165 per mile as obtained from [15]. $D_{tot}$ is the total distance that the ESTs drive annually shipping the batteries between the BESS and the EVCSs:

$$D_{tot} = \sum_{i=1}^{EVCS_{tot}} l(i)N_{AS}(i)$$ (11)

where $l(i)$ represents the distance between the BESS and the $i^{th}$ EVCS, while $N_{AS}(i)$ is the number of shipments the $i^{th}$ EVCS requires annually. $\varphi$ and $\omega$ are the annual maintenance cost percentage of the investment amount for ESTs and batteries respectively. $\psi$ is the annual salary for EST fleet operators, usually in the average of $70k$ [16].

To summarize, Table 1 presents the list of main model parameters and variables, as well as some typical values and justifications.

**Table 1.** List of symbols used in the model.

| Parameter        | Explanation                                                                 |
|------------------|-----------------------------------------------------------------------------|
| $t_{req}(i)$     | Time when a battery is needed at the $i^{th}$ station                        |
| $N_B(i)$         | Number of Batteries at the $i^{th}$ station                                  |
| $N_{EST}$        | Number of ESTs                                                               |
| $B_{cap}$        | Battery capacity                                                             |
| $d(i)$           | discharge rate for the $i^{th}$ station                                      |
| $t_s(i)$         | Truck Start Time to the $i^{th}$ station                                     |
| $t_e(i)$         | Truck End Time returning from the $i^{th}$ station                          |
| $t_T(i)$         | Travel time for the Truck from the BESS to the $i^{th}$ EVCS                |
| $N_{B,F,D}(i)$   | the number of batteries that is equivalent to a full day demand for the $i^{th}$ station |
| $d$              | Discount rate = (5, 8, 10) %                                                 |
| $\gamma_{EST}$   | The economic life of EST = (5,15,25) years                                   |
| $\gamma_{B}$     | The economic life of battery = (5,15,25) years                              |
| $\gamma_{plant}$ | The economic life of plant = (50) years                                      |
| $\mu$            | Price of each EST ($) = 150k – 200k [12][13]                                 |
| $\tau$           | Price of each battery ($) = 5MWh*$100/1kWh = $50,000 [14]                   |
| $\sigma$         | Trip cost ($/mile) = 1.5kWh/mile * $0.11/kWh = $0.165 [15]                  |
| $\varphi$        | Annual maintenance cost % of EST investment cost ($) = 10% of ($C^{EST}$)   |
| $\omega$         | Annual maintenance cost % of Batts investment cost ($) = 10% of ($C^{B}$)    |
| $\psi$           | EST operator salary ($) = 70k/year on avg. [16]                              |
| $D_{tot}$        | The annual total distance ESTs drive shipping the batteries between the BESS and EVCSs |
| $l(i)$           | Distance between the BESS and the $i^{th}$ EVCS                             |
| $N_{AS}(i)$      | The number of shipments the $i^{th}$ EVCS requires annually                 |

3. Results and discussions
The optimization problem defined in the previous section is a standard linear programming (LP) problem except two modifications. Firstly, the simulation of the EVCS battery energy levels for one year need to be conducted to identify the feasible number of ESTs. Secondly, the two control variables are integers. Under the constraints and conditions, applying MATLAB LP function yields a result of the optimum combination of 128 batteries as the total number of batteries (64 batteries at the EVCSs distributed as in Fig. 4 to meet the stations demand and the same number at the BESS to save the
excess energy from the wind farm), and 14 ESTs required to fulfil the logistics operation of the BESS. This combination produces the minimum annual cost of about $2.78 million under the case of 5% discount rate, 25 years lifetime of ETS and other parameters summarized in Table 1.

To see the effects of the discount rate and EST life time on the minimized annual costs of the logistics system, we chose three different values of each parameter and compare the results in Table 2 and Fig. 5. In these cases the battery life time is fixed at 25 years. The prices of each 5 MWh battery and EST are $50 k and $150 k. It can be seen that optimal numbers of batteries and ESTs are relatively insensitive to the parameter changes. This is because the minimum numbers are required for operation.

Table 2. Optimization results under different discount rates and EST lifetimes.

| Discount rate | EST lifetime | # of batteries | # of EST | Annual cost ($, millions) |
|---------------|--------------|----------------|----------|--------------------------|
| 5%            | 5 years      | 128            | 14       | 3.1145                   |
|               | 15 years     | 124            | 14       | 2.7975                   |
|               | 25 years     | 128            | 14       | 2.7784                   |
| 8%            | 5 years      | 130            | 14       | 3.3337                   |
|               | 15 years     | 130            | 14       | 3.0531                   |
|               | 25 years     | 130            | 14       | 3.0044                   |
| 10%           | 5 years      | 128            | 14       | 3.4574                   |
|               | 15 years     | 128            | 14       | 3.1795                   |
|               | 25 years     | 128            | 14       | 3.1348                   |
Figure 5. Annualized costs under different discount rates and EST lifetimes. It is expected that the longer the EST lifetime and the lower the discount rate, the lower the annualized cost. Similarly, in Table 3 and Fig. 6, we compare the minimized annual costs under different values of the discount rate and battery life time. In these cases the EST life time is fixed at 25 years. The prices of each 5 MWh battery and EST are $50 k and $150 k.

Table 3. Optimization results under different discount rates and battery lifetimes.

| Discount rate | Battery lifetime | # of batteries | # of EST | Annual cost ($, millions) |
|---------------|-----------------|----------------|----------|---------------------------|
| 5%            | 5 years         | 126            | 14       | 3.7695                    |
|               | 15 years        | 126            | 14       | 2.9213                    |
|               | 25 years        | 128            | 14       | 2.7784                    |
| 8%            | 5 years         | 130            | 14       | 4.0235                    |
|               | 15 years        | 126            | 14       | 3.1116                    |
|               | 25 years        | 130            | 14       | 3.0044                    |
| 10%           | 5 years         | 130            | 14       | 4.1544                    |
|               | 15 years        | 128            | 14       | 3.2711                    |
|               | 25 years        | 128            | 14       | 3.1348                    |

Figure 6. Annualized costs under different discount rates and battery lifetimes. The longer the battery lifetime and the lower the discount rate, the lower the annualized cost. Further, we analyze the effects of EST costs and life times on the minimized annualized costs. The results are shown in Table 4. In these cases the discount rate, the battery lifetime, and battery price are fixed at 5%, 25 years, and $50 k, respectively.

Table 4. Optimization results under different EST costs and lifetimes.

| EST Cost ($) | EST lifetime | # of batteries | # of EST | Annual cost ($, millions) |
|--------------|--------------|----------------|----------|---------------------------|
| 100k         | 5 years      | 124            | 14       | 2.8486                    |
|              | 15 years     | 124            | 14       | 2.6601                    |
|              | 25 years     | 128            | 14       | 2.6588                    |
| 125k         | 5 years      | 124            | 14       | 2.9644                    |
|              | 15 years     | 128            | 14       | 2.7630                    |
We also show the effects of battery costs and life times on the minimized annualized costs in Table 5. In these cases the discount rate, the EST lifetime, and EST price are fixed at 5%, 25 years, and $150 k, respectively. It is expected that the higher the battery price and the shorter the battery lifetime, the higher the annualized cost.

Table 5. Optimization results under different EST costs and lifetimes

| Battery Cost ($) | Battery lifetime | # of batteries | # of EST | Annual cost (\$, millions) |
|------------------|------------------|----------------|----------|--------------------------|
| 50k              | 5 years          | 126            | 14       | 3.7695                   |
|                  | 15 years         | 126            | 14       | 2.9213                   |
|                  | 25 years         | 128            | 14       | 2.7784                   |
| 75k              | 5 years          | 126            | 14       | 4.8120                   |
|                  | 15 years         | 124            | 14       | 3.5103                   |
|                  | 25 years         | 126            | 13       | 3.2042                   |
| 100k             | 5 years          | 128            | 14       | 5.9208                   |
|                  | 15 years         | 126            | 14       | 4.1582                   |
|                  | 25 years         | 126            | 13       | 3.7427                   |

According to the results presented in Tables 2 thru 5, one can first see that although the values of the five parameters (discount rate, EST lifetime and price, and battery lifetime and price) are selected from a fairly wide range, the optimized combination of battery and EST numbers does not vary much. In the optimized results, the number of batteries at each EVCS is primarily determined by the EVCS’s demand profile, while the number of ESTs in the logistics systems is the minimal requirement for normal operation. In this study, we let EST always have a higher price than battery, which contributes to the results that the algorithm always keeps the EST number at its lowest. In fact, there is a trade-off between EST and battery numbers. More ESTs can enable more frequent shipments between the BESS and the EVCSs and therefore reduce the total number of batteries needed.

4. Conclusions
We have demonstrated an optimization framework for the optimal design of a battery-powered EVCS network’s logistics system with minimum costs. The EVCS network is independent from the electrical grid and can supply power to EVCSs from renewable energy resources stored in a BESS. Different from traditional battery farms, this work proposes that in the future, the technology will enable portion of the BESS to be mobilizable; and ESTs can ship the batteries between the BESS and EVCSs. Given the demand at each EVCS and the supply at the BESS (assumed to be infinity in this work), the problem is essentially logistics system planning. The results in this paper shows that even under parameter uncertainties, the system characteristics (i.e. numbers of battery and EST) are relatively robust, reflecting the system’s operational requirements. The results of this work can help potential stakeholders make business or policy decisions. Future work can be done to include stochastic and/or real time travel times to the model and consider a finite and time-dependent supply profile.

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