Modelling Second-Life Batteries as the Energy Storage System for EV Charging Stations

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***Abstract*—This paper introduces a model for using second-life batteries (SLBs), retired from electric vehicles (EVs), as the energy storage system (ESS) in order to improve the profitability of a public charging station. Furthermore, the introduced model significantly flattens the peak loads to the grid introduced by the operation of charging stations. The reinforcement learning algorithm used here does not depend on forecast data, and learns to make optimal scheduling decisions for charging the ESS and the EVs online, either charging from the ESS or from the power grid. The implemented model is simulated using real data and compared to another charging scheduler. The resulting charging station system proves to be more profitable with the inclusion of the ESS and also helps flatten the electrical energy load on the power grid during on-peak times. Additionally, by modelling the battery degradation of the SLBs for each charge and discharge cycle, it is shown that the life time of these batteries can be extended. Therefore, it is a viable use for these batteries as they can fulfill the requirements of the ESS for a year before their charge capacity falls below the 50% mark that defines their end of life.**

***Index Terms*—Electric vehicles (EV), reinforcement learning (RL), scheduling, electric vehicle charging infrastructure, energy storage systems, second-life batteries**

I. Introduction

With large automobile brands Volkswagen and Audi announcing their plans to stop the development of internal combustion engine vehicles by 2026 [1], [2], and Ford investing $30 billion into electric vehicle research by 2025 [3], there is no more doubt that the future of vehicles is electric. In dense urban areas, private parking garages and access to private charging stations is more sparse and alternative charging options need to be considered for the growing number of electric vehicles (EVs) on the road. The German Association of Energy and Water Industries states that there are only 40,000 public and semi-public charging areas in Germany, with a seventh of these being DC fast charging stations [4], however the European Commission and the Nation Platform for Electric Mobility in Germany recommend 150,000 and 77,100 charging stations, respectively [5]. This suggests a considerable gap in the market for electric charging stations in Germany.

To motivate more charging stations opening across the world their profitability needs to be ensured. Using smart scheduling algorithms is essential to this goal, however that alone does not guarantee the ability to stay competitive with the prices. Another challenge with electric vehicle charging stations is the additional load they require from the electric grid. Uncoordinated EV charging significantly increases the peak load which could exceed the capacity of existing electricity distribution infrastructure [6]. This additional load could lead to problems with the power grid and in the worst case result in a blackout. Energy balancing and flattening the peak electricity use is very important for the electric grid to avoid such problems. The inclusion of an energy storage system (ESS) in this work improves both the profitability and energy balancing of a charging station as it allows the electrical energy to be bought and stored during off-peak hours, and at a lower cost, to be used during the more expensive on-peak hours.

An argument used against EV adoption is the environment impact of the batteries. Lithium-ion batteries are currently the most used batteries in EVs [7]. As with all rechargeable batteries, there is a limit to the charging cycles the battery can undergo before the battery degrades. Additionally, these batteries require lithium and cobalt which are limited resources. For these batteries to have a future, recycling these materials becomes of paramount importance. Additionally, those rare metals increase the price of the battery to up to 30% of the cost of the EV [8]. As a result, the life cycle of an EV battery is of great importance and an area where there is room for improvement. It is challenging to recycle lithium-ion batteries. They are larger and heavier than other batteries, their construction is more complex, and if they are not correctly disassembled it can be dangerous [8]. A battery is retired from an EV at about 70% of its nominal charge capacity [8], *i.e.* a battery with a factory capacity of 40 kWh can still store 28 kWh after its removal from an EV. Therefore, a reasonable option is to reuse these batteries for other applications to extend their lifespan, *i.e.* second life.

By combining these two application areas we aim to solve two problems simultaneously. The reuse of EV batteries to lengthen their lifespan, and the flattening of the electric usage peak by including an energy storage system in an EV charging station. The goal of this work is twofold. The first goal is to quantify the benefits of including an ESS in a charging station. The second is to investigate the effect of the battery degradation on the ESS if it is made up of second-life batteries (SLBs).

These problems are known, therefore other literature has approached them, for example, Erick and colleagues have two publications focusing on Q-learning methods to solve the scheduling problem of an EV charging station with a photovoltaic energy source, and battery, [9] and [10]. These works set a groundwork for the problem, however the method used relies on forecasting the electricity price and EV arrival data, which introduces uncertainty into the resulting Q-learning policy. Additionally, their work does not consider using second-life batteries and their degradation. The reinforcement learning (RL) algorithm introduced in [11] solves the scheduling problem for a charging station model-free, meaning the data is not forecast, it is fed to the algorithm in real-time and the RL agent needs to learn to make optimal decisions based on the information available at the current and previous times. However, [11] does not consider an ESS in their system.

As we also aim to model the SLB degradation, there is also interest in existing research on the modelling of second-life batteries and their efficacy in building energy storage systems, these include [12]–[16]. Additionally, [17] and [18] highlight the advantages of including an ESS in a charging station. To the best of our knowledge there is no work investigating the inclusion of SLBs in a charging station and what effect the battery degradation has on the system.

Paper Organization: Section II of this paper presents the system model used to solve this problem. Followed by Section III with the reinforcement learning method used is described. In Section IV the experiments and their setup is introduced. This section is also where the results of our system are presented. Finally, Section V concludes the paper.

II. System Model

When an electric vehicle requires charging it can be brought to a charging station and left there for a set amount of time to be charged at the current charging price. In this model the EVs enter the charging station independent of a model (using historical data) and stay for a defined amount of time. The public charging price r_t in \$/kWh is determined by the charging station for all EVs arriving at time t and does not change for them once they are at the station. The price

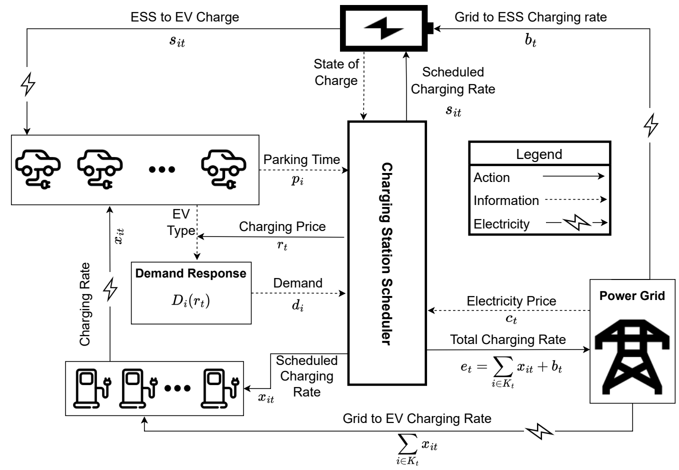

Fig. 1. Charging Station System.

can be different for EVs arriving at different times, similar to how gas prices work at a gas station but with a shorter fluctuation time. When the EVs arrive their charging demand is determined by the demand response (DR) function $D_i(\cdot)$ of each EV i. The demand response function is unique to each type of EV and is in response to the price r_t, so each EV sets its charging demand as $d_i = D_i(r_t)$. For more information on the DR functions and how they can differ for different EVs see [11].

Figure 1 shows the flow of information, the actions chosen by the scheduler and the electric power transmission. There are three parts, the SLBs, the EVs and the utility company.

At each time step $t \in \{1, \ldots, T\}$ there are EVs arriving at the charging station $i \in \mathcal{I}_t$ with a certain charge demand d_i and parked EVs $\mathcal{J}_t$ that have arrived previously to time t. The total number of EVs at the station that still require charging are denoted by $\mathcal{K}_t := \mathcal{I}_t \cup \mathcal{J}_t$. All EVs have a defined parking time p_i and therefore from their arrival time t_i^a until their departure $t_i^a + p_i$ their charge demand must be satisfied.

The charging station purchases electric power from the utility company at price c_t to charge the ESS and the EVs. The actions chosen by the scheduler are the charging price r_t, the charging rates from the grid to the ESS b_t and from the grid to the EVs x_{it}, and the discharging rate from the ESS to the EVs s_{it}. These four parameters are determined by reinforcement learning and they affect the remaining demand of the EVs, as well as the parking time of the EVs, and the state of charge of the ESS SoC_t.

To reach the charging demand of the EVs the scheduler decides on the charging rate x_{it} in kWh of each EV $i \in \mathcal{K}_t$ at time t. These rates have the following constraints

$$x_{it} \leq x^{\max}, \quad t = 1, \ldots, T, \quad \forall i \in \mathcal{K}_t, \tag{1}$$

$$\sum_{i \in \mathcal{K}_t} x_{it} \leq e^{\max}, \quad t = 1, \ldots, T, \quad \forall i \in K_t, \tag{2}$$

where $x^{\max}$ and $e^{\max}$ are the maximum individual and aggregate charging rates, respectively.

When the EV departs from the charging station it is billed $r_t D_i(r_t)$. This means the charging station is getting paid $\sum_{i \in \mathcal{I}_t} r_t D_i(r_t)$ and in turn pays $c_t(\sum_{i \in \mathcal{K}_t} x_{it} + b_t)$ to the electricity provider every time step t.

When using SLBs as storage systems, an important consideration is to avoid further degradation. The aging process of a battery is largely influenced by the minimum and maximum state of charge allowed to be reached [8]. Typically, the battery management system (BMS) is responsible for ensuring that the battery does not reach certain specific states of charge, which depend on the intrinsic characteristics of the battery and can have adverse effects. In automotive applications, these values are usually quite large, between 10% and 95% of the battery's rated capacity. This is due to the requirement that they must provide mobile service, in which case a high level of available energy means a longer driving range. In stationary applications, this characteristic is not as critical, and the tendency is to keep the range smaller to ensure a longer service life. Therefore, the following constraint prevents the battery from exceeding the maximum and minimum state of charge (SoC)

$$SoC_{\min} \leq SoC_t \leq SoC_{\max}, \tag{3}$$

where $SoC_{\min}$ is the minimum value for the state of charge and $SoC_{\max}$ is the maximum value for the state of charge. In order to make sure the charging demand is fulfilled during the parking time, the following constraint is given

$$\sum_{t=t_i^a}^{t_i^a + p_i} (x_{it} + s_{it}) \geq d_i, \tag{4}$$

where s_{it} is the discharge rate from the ESS to EV i. The discharge rate s_{it} is constrained by

$$s_{it} \leq h^{\max}, \; t = 1, \ldots, T, \tag{5}$$

where $h^{\max}$ is the upper bound of s_{it}. The goal is to minimize the costs of the charging station, therefore it is important to consider the initial capital cost and the operating cost of the system. These costs are combined to a total cost of

$$C_{\text{total}} = C_{ESS} + C_G, \tag{6}$$

where C_{ESS} are the initial capital costs of the ESS and C_G includes all the costs associated with the operation.

A. *Second-life-Battery Degradation Model*

In order to understand and plan with the SLBs, the health of the battery needs to be defined. The state of health (SoH) of the battery is not the same as the state of charge (SoC) of the battery. The former is the volume of available power left in the battery, *i.e.* the ratio of current achievable capacity with the initial capacity

$$\text{SoH} = \frac{C_{\text{current}}}{C_{\text{nom}}},$$

where C_{current} is the current capacity of the battery, and C_{nom} is the nominal capacity. SLBs are defined by an SoH of 80% to 50% [8]. The SoC on the other hand is a percentage that reflects the remaining capacity of the battery, which is the ratio of the remaining capacity to the initial capacity. To calculate the SoC of a battery, the definition from the United States Advanced Battery Consortium (USABC) [19] is widely used. Here

$$SoC = \frac{Q_m - Q(I_t)}{Q_m},$$

where Q_m is the maximum discharge capacity of the battery when discharged at a constant current I and $Q(I_t)$ is the power released from the battery at a standard discharge current at time t.

The SoC cannot be directly measured, it can only be estimated using the terminal voltage, charge and discharge current, internal resistance, and other parameters. These values however also fluctuate based on the batteries age, the temperature of the environment and the driving status of the vehicle. Accurate estimation of this value is in itself a difficult research problem.

In this work the ampere-time integration method [20] is used to estimate the SoC of the lithium-ion batteries as it is widely used by the BMS. This method does not consider the mechanism inside the battery, instead it calculates the total power flowing into and out of the battery by integrating the current over a certain time frame and compensating for other factors through additional linear terms. The SoC at time t is thus

$$SoC_t = SoC_0 - \frac{1}{C_E} \int_0^t I(\tau) \gamma \, d\tau,$$

where SoC_0 is the initial charge of the battery, C_E is the capacity rating of the battery, $I(\tau)$ is the charge/discharge current of the battery at time τ, and γ is the efficiency coefficient. The temperature coefficient represents the power dissipation in the battery during the charging and discharging process and depends on the charge/discharge multiplier and temperature correction coefficient.

The ampere-time integration method is simple and reliable

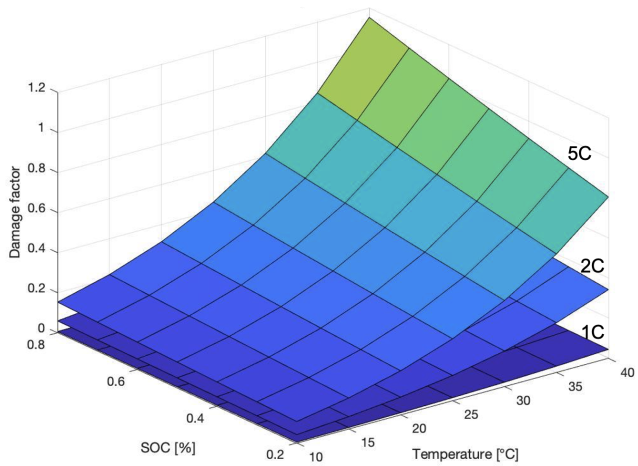

Fig. 2. Battery Aging Model - Damage Factor.

and can be implemented in real-time to estimate the battery's state of charge. However, the method is an open-loop detection, meaning that if there is an inaccuracy in the initial charge value this error will gradually accumulate.

Another important factor about the battery cycling parameter is the battery discharge rate C. The Lithium-ion battery charge and discharge rate is equal to the charge and discharge current divided by the rated capacity of the battery. For example, when a battery with rated capacity of 100 Ah is discharged with 20 Ah, its discharge rate is $0.2C$.

The weighted throughput aging model from [21] is used in this work. The standard battery cycle life refers to the number of charge and discharge cycles a battery can withstand before its capacity decays to a certain specified value under a certain charge and discharge regime. One cycle means one full charge and one full discharge.

The aging model Q_{loss} in [21] investigated the effect of battery life with respect to current charging rate, state of charge, temperature and Ah-throughput. The percentage of capacity loss can be defined as

$$Q_{loss} = \delta \cdot (C_{\text{eq}})^z, \tag{7}$$

where C_{eq} is the Ah-throughput, or equivalent capacity, which is expressed as C_{eq}=(cycle number)×(depth of discharge)×(full capacity) and z is the power law exponent that represents the dependence of throughput C_{eq}. The severity function δ can be expressed as

$$\delta = (\alpha \cdot SoC + \beta) \cdot \exp\left(\frac{-E_a + \eta I_c}{R_g \cdot (T + 273)}\right), \tag{8}$$

where α and β define the SoC dependence, E_a is the activation energy equal to 31,500 J mol^{-1}, I_c is the current charging rate, R is the universal gas constant, and T is the battery temperature. The optimal values of α and β are parameterized using experimental data [21], see Table I.

TABLE I
CAPACITY LOSS PARAMETER

SoC	α	β
$SoC < 45\%$	2896.6	7411.2
$SoC > 45\%$	2694.5	6022.2

Finally, the severity or damage factor, can be derived from Q_{loss}. If the end of life a battery is defined as 50% *i.e.* $Q_{loss} = 50$, the throughput under different operation coditions can be calculated as

$$\gamma = \left[\frac{50}{\delta(SoC, T, I)}\right]^{\frac{1}{z}}.$$

In Figure 2 we can see that the the higher the current and temperature of the environment, the greater the damage to the battery. If we assume that the batteries are stored in a temperature controlled environment at the charging station, then the current at which the batteries are charged and discharged is the variable we are interested in to monitor the degradation of the batteries.

B. Markov Decision Process

Combining the system model and battery degradation defined above, a novel Markov decision process can be defined that can be solved using reinforcement learning.

- System State: The state at time t is
$$S(t) = (SoC_t, K_t, \tilde{d}_i^t | \forall i \in K_t, \tilde{p}_i^t | \forall i \in K_t), \tag{9}$$
where SoC_t is the state of charge of the ESS at time t, K_t is the set of all EVs at the station, $\tilde{d}_i^t$ denotes the residual charging demand of vehicle i, and $\tilde{p}_i^t$ is the residual parking time of vehicle i at time t. Together the state S_t of the charging station and the cost of electricity c_t make up the environment.
- Action and transition: The action space is
$$A(t) = (r_t, x_{it} | \forall i \in K_t, b_t, s_{it} | \forall i \in K_t),$$
where r_t is the charging price of the EV station at time t, x_{it} is the charging rate of the EVs from the power grid, b_t is the charging rate of the ESS from the power grid, and s_{it} is the charging rate of the EVs from the ESS. Under the scheduling of x_{it} and s_{it} we have
$$d_i^{t+1} = d_i^t - x_{it} - s_{it} \qquad \forall i \in J_t, \tag{10}$$
$$d_i^{t+1} = D_i(r_t) - x_{it} - s_{it} \qquad \forall i \in I_t, \tag{11}$$
$$\tilde{p}_i^{t+1} = \tilde{p}_i^t - 1 \qquad \forall i \in J_t, \tag{12}$$
$$\tilde{p}_i^{t+1} = p_i - 1 \qquad \forall i \in I_t. \tag{13}$$

The charging rate and the discharge rate of the battery we describe by the c-rate

$$b_t = \frac{1}{C_E}\int_0^t I_c(\tau)d\tau, \tag{14}$$

$$s_{it} = \frac{1}{C_E}\int_0^t I_d(\tau)d\tau. \tag{15}$$

By including the charging and discharging rate into the SoC ampere-time integration method we have

$$SoC_{t+1} = SoC_t + (b_t - s_{it})/C_E(1 - Q_{loss}). \tag{16}$$

- Reward:
The charging station collects the payment r_t from the EVs and pays the electricity cost c_t to the utility company for the charges x_{it} and b_t. The total costs incurred by the ESS are also considered in this model, as the result the reward is given by

$$R(S_t, A_t) = \sum_{i\in I_t} r_t D_i(r_t) - c_t \sum_{i\in K_t} x_{it} - c_t b_t - C_{\text{total}}, \tag{17}$$

where the C_{total} is the purchase and the maintenance cost of the second-life batteries.

III. Reinforcement Learning - A3C

To solve the scheduling problem the Asynchronous Advantage Actor-Critic (A3C) approach is used. This approach contains two networks: the actor-network and the critic-network. The local network and global network models are trained alternately, that is, the global network node space representation is fixed during local network training, and no communication is required after the local training. The vector is fixed and no communication is needed; when the local network training is finished, the results are passed to the global network, while other local networks are not affected. The general idea is to increase the number of local training entities and reduce the frequency of synchronous updates.

The goal is to find the optimal action A by solving the reward

$$G_t = R_t + \gamma R_{t+1}, \tag{18}$$

where γ is the attenuation coefficient. Here we don't need to calculate the exact return value, instead we use the TD_{error}

$$TD_{error} = r + \gamma V(s_{t+1}, a_{t+1}) - V(s_t, a_t), \tag{19}$$

where $V(s_t, a_t)$ is the state value function, or V-function, which is estimated by the critic. The TD_{error} is used to update the actor-network. The policy gradient formula is given by

$$\nabla_\theta J(\pi) = E[A(s,a)\nabla_\theta \log(\pi(a|s)], \tag{20}$$

where $\pi(a|s)$ is the policy function. This means that

$$A(s,a) = r + \gamma V(s_{t+1}, a_{t+1}) - V(s_t, a_t), \tag{21}$$

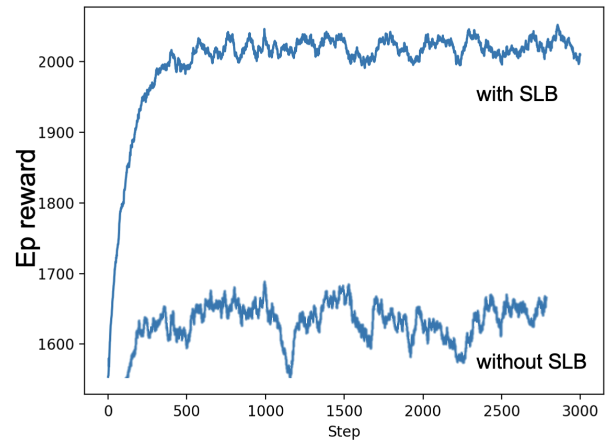

Fig. 3. Revenue with and without Second Life Battery over a month.

so we can use the TD_{error} as the weight value to update the policy in the actor-network. In this network, the input of the network is the current state, the output of the network is the probability of each action.

As for the value-based critic network, it is intuitively understood that its role is to evaluate whether the chosen action is good or bad. The input of the critic network is the current state, the reward and the state at the next time step. The output of the network should be the result of the evaluation of the action, i.e., the TD error. In order to update the critic-network, we need to minimize the loss

$$L_{\text{loss}} = TD^2_{\text{error}} = (r + \gamma V(s_{t+1}, a_{t+1}) - V(s_t, a_t))^2. \tag{22}$$

In addition, to improve the model training efficiency and reduce the computational effort, the same two methods introduced in [11] are used. One is the action reduction function and another one is linear function approximation. For more information on actor-critic networks and detail on the above, see [22].

IV. Experiments

Two experiments were conducted for this work to answer two questions: Does adding an ESS improve revenue and to what extent? and What are the repercussions of using second-life-batteries for the ESS with regards to the battery degradation? These experiments were run using historical electricity prices from San Francisco [23]. The EV arrivals were taken from [24], which is a data set including the total number of electric vehicle arrivals at Richards Ave station for 30 days. Note that in order to predict battery degradation over a longer time period, additional EV arrival data was required. To supplement this data, the Poisson distribution was used and the parameters of the distribution were generated using

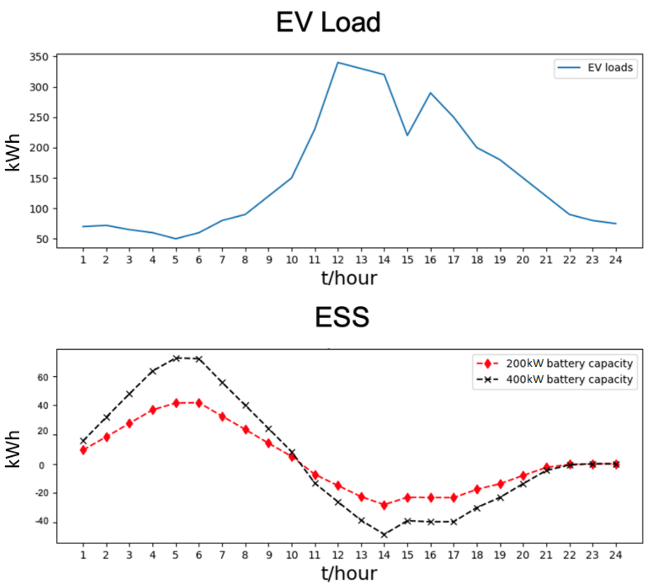

Fig. 4. EV and ESS Load over 24 hours.

this data.

The demand response function and system parameters used in this work are taken from [11]. Additional parameters for the RL algorithm can be found in Table II. The problem was implemented in Python and solved using PyTorch. Wang et. al [11] made their code available on GitHub [25] and was used as the building block for the implementation.

TABLE II
PARAMETER LIST

Parameter name	Parameter value
Attenuation coefficient γ	0.9
Number of workers	4 (CPU count)
Activation function	tanh
Output function	softmax
Time step	5 minutes
Learning rate l_r	0.0001
Smoothing constant	(0.92, 0.999)
ϵ	0.000001
Weight decay	0

A. Including ESS

The first question to answer is whether or not the inclusion of an ESS in an EV charging station is a profitable venture. Figure 3 clearly demonstrates that with the SLB in the system, the revenue, or episode reward is increased by 400 units on average over the time period of one month. The ESS behaves as intended, as demonstrated in Figure 4. This figure shows the load over a typical 24 hour period. The ESS is a system made up of many EV batteries, over a charging station network

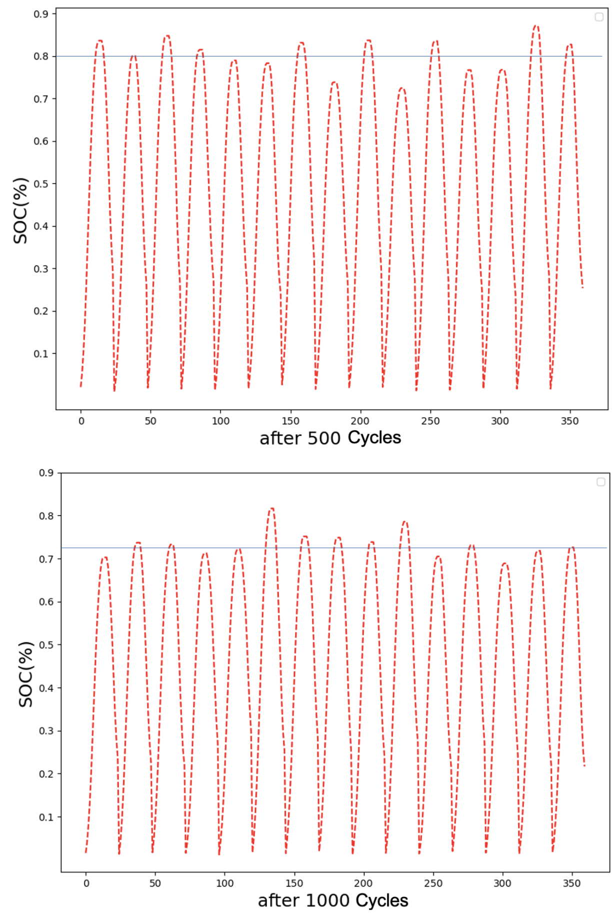

Fig. 5. SoC after 500 and 1000 Cycles.

and the total capacity of these systems were set to 200 kW and 400 kW for this study. When the EV load and the price of electricity are lower, at the beginning of the day, the ESS charges and when the EV load is high the ESS discharges. This means that during peak electricity hours the charging station is using the ESS storage as its electricity source, instead of buying electricity from the grid at the higher price. This is what results in not only higher revenue for the charging station, but also lower electricity demand on the power grid during peak hours.

B. Second-life-Batteries

The depth of discharge was kept at a constant value and a 2C charge/discharge rate was used. Figure 5 show that after 500 cycles the SoC drops to 80% and after 1000 cycles it drops to just above 70%. If we define the end of life as 50 percent of it's original capacity, the SLB would need to be changed after one year. This tells us that using SLBs in an

ESS is a feasible and cost effective way to extend the lifetime of retired EV batteries.

V. Conclusion

Using the model presented in this paper, we have shown that including an ESS is a profitable choice for an EV charging station. The RL algorithm was able to generate a policy that charged the ESS during off-peak time and therefore at a cheaper electricity price and use this charge to charge the EVs during on-peak times. This is advantageous for the charging station, as it brings in more revenue, and it is also advantageous for the power grid that had a reduced load from EVs during the on-peak times.

This work also shows that SLBs from EVs can be used in charging stations as the ESS. Their capacity after their first life is still sufficient for an ESS. Due to the environmental impacts that Lithium-ion batteries present, SLBs are a good solution to extend the life span of the batteries. While battery degradation is a concern for reused batteries, our model was able to show that despite the degradation, the batteries have a sufficient SoC to be used for a year at a charging station.

Beyond the operational, maintenance and purchasing costs of the SLBs, logistic considerations and costs are incurred at the end of the usage of these batteries to dispose of them. Further work could include these considerations, as well as including vehicle to grid systems, which would have similar benefits. This problem can also be extended to consider scheduling on a microgrid scale, with the inclusion of renewable resources for example.

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