IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received June 18, 2019, accepted July 14, 2019, date of publication July 22, 2019, date of current version September 24, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2930233

Electric Vehicles Battery Wear Cost Optimization for Frequency Regulation Support

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ABSTRACT Due to their capacities and quick response, Electric Vehicle (EV) batteries can be used to support a number of power grid services and form a Vehicle-to-Grid (V2G) system. When aggregated and properly managed EV batteries can provide important ancillary services such as peak load levelling and frequency regulation. EVs can also provide various demand response services and help in renewable energy integration. The major challenge for having a wide-scale V2G system to effectively provide the above services is the availability of power which is limited by the battery degradation and the battery cycle life. The battery cycle life is inversely proportional to the charge/discharge cycles the battery goes through during its operation. Therefore, the charge/discharge operation should be optimized to maximize the benefit for both the EV owners and the grid operator. In this paper, we develop an EV charge/discharge optimization model that incorporates frequency regulation and electricity prices from both real and forecasting models into the objective function of the model. We develop a prediction and optimization model to reflect the effects of dynamic and static electricity and regulation prices on the battery cycle life. We present a case study for the charge/discharge scheduling problem utilizing real, predicted regulation and electricity hourly pricing.

INDEX TERMS Aggregator, battery degradation, charge scheduling, mixed integer linear programming, Vehicle-to-Grid (V2G), frequency regulation.

I. INTRODUCTION

The state of the art in the electrified transportation system is a standard shift from conventional Internal Combustion Engine (ICE)-based vehicles to more reliable, efficient and cleaner electrified vehicles [1]. Based on several feasibility studies, Electric Vehicle (EV) batteries can be used to deliver power back to the grid and provide support when the vehicles are parked and connected to the grid [2], [3]. The power from EV batteries can be aggregated and then fed back to the grid to participate in demand-side management programs and provide various ancillary services such as frequency regulation, Volt-VAR control and renewable energy integration in a distributed Vehicle-to-Grid (V2G) infrastructure [4]. V2G is a technology that facilitates the interaction of EVs with the power grid to allow charging or discharging based on certain control algorithms to provide various important grid services [5]. V2G involves algorithms and techniques that can be implemented in the EVs, the charging stations, user control systems, grid control centers, grid generation, and distribution systems. These V2G sub-systems exchange information and data required to implement the techniques and algorithms for the V2G applications. Other applications of V2G include the provision of demand response and integration of renewable energy with the grid.

A typical scenario of a V2G service is the communication of the power control commands from the grid operator to the EV user and the charging station where the usage profile and the preferences are obtained. Subsequently, EVs connect to charging stations to either charge or discharge. Owing to the fast charging rate of the EV batteries, in this paper, we focus on frequency regulation service which is the most promising and practical service among other V2G applications. Frequency regulation service is needed to maintain a stable grid frequency when variations in the power generated and loads take place [6]. This service is important to maintain the power system security and avoid additional costs associated with industrial production, equipment damage and market distortion [7]. Frequency regulation is currently performed by ramping up or down fast turning generators that bid into the market. This is provided by generators that are contracted to provide the nominal power with the ability to adjust their power levels based on the regulation signal from the grid operator [8]. However, the traditional generators may have a slow response time and limited ramp rate, thus their performance is not quite satisfactory [9]. On the other hand,

The associate editor coordinating the review of this manuscript and approving it for publication was Kai Li.

EVs batteries can easily be controlled and respond faster and thus can help support frequency regulation. This can be done by charging or discharging EV batteries when the grid frequency increases or decreases [10] respectively.

EVs participation in V2G services can be limited by a number of factors including energy constraints, users behaviours and battery degradation. Other EV challenges include limitations on the batteries' energy density, the need for new charging infrastructure and the time required for charging or discharging the batteries [11]. In this paper, we focus on battery degradation since batteries can undergo excessive charge/discharge cycles. These excessive cycles can over time impact the lifetime of the batteries. Based on that, the cost of battery degradation is important to the EV owner since the battery replacement cost can be very high compared to the overall EV cost. The main aim of the paper is to study the degradation of the EV batteries when providing frequency regulation. The grid model, voltage and their impact on the battery degradation are out of the scope of this paper.

In [4], we presented an optimization model which uses the frequency regulation and real-time electricity prices to minimize the batteries' wear cost. In [12], we developed an iterative algorithm to predict the effect of static and dynamic electricity and frequency regulation prices on the battery cycle life (C_L).

Unlike [4] and [12], which only considered an optimization model that can either use the frequency regulation or real-time electricity prices to minimize the batteries' wear cost, in this paper, we present a holistic approach that combines effects of [4], [12], long-term electricity price prediction on C_L and the battery degradation cost. We do this by introducing an iterative algorithm that combines the current and predicted static and dynamic electricity prices with the frequency regulation signals on C_L and by integrating the forecasting mechanism into the charging and discharging optimization models described in [4] and [12]. Our new model shows that long-term forecast price prediction helps in analyzing the effect of electricity and frequency regulation prices on the EV battery cycle life. We simulate the forecast and optimization model to provide a realistic scenario and an insight into the effect of the charging-discharging process on the EV battery. In this paper, we show that EV owners can be made aware of the long-term effects before participating in the V2G services. In addition, we include the effect of C_L when determining the optimum charge/discharge processes, State of Charge (SOC) profile over the charging/discharging periods and the impact of the wear cost on the batteries. These important aspects are new and have not been previously discussed in the literature or in [4] and [12].

A. PAPER CONTRIBUTIONS

The major contributions of this paper can be summarized as follows:

1) We present an Electric Vehicle Charge/Discharge (EVCD) model that incorporates frequency regulation signals, real-time and predicted prices into its operation.
2) We present a realistic case-study for the charge/discharge scheduling problem using hourly real frequency regulation and hourly electricity prices.
3) We present a novel iterative algorithm that can predict the effect of static and dynamic electricity and regulation prices on the battery C_L.
4) We propose a forecasting model and incorporate the results (i.e. forecast prices) obtained into the EVCD model using the developed case-study.
5) We present a comprehensive analysis to depict the hourly SOC profile over the charging period in addition to optimal charge/discharge schedule.

B. PAPER ORGANIZATION

The remainder of this paper is organized as follows, Section II presents the related work. Section III presents the EV charge/discharge model. Section IV presents the forecast model and Section V presents the proposed iterative framework with dynamic cycle life. Section VI presents the results and analysis. Finally, in Section VII, this work is concluded.

Table I. shows the summary of notations used in this paper.

II. RELATED WORK

The use of EVs to support various power grid applications in a V2G system has been widely discussed in the literature. An early work by [13] introduced the idea of V2G, the authors have focused mainly on how EV batteries can be connected to the power grid. In a later study [14], the authors have identified various feasible services that can be derived from connecting EVs to the Grid. Tomić and Kempton [15] have analyzed business models and potential profit based on V2G support compared to existing grid regulation methods, the economics of the V2G services and how to manage the technology in the new market. The authors, however, did not consider the degradation and cycle life loss associated with EV batteries when participating in the V2G process.

Battery cycle life and degradation analysis have also been considered in a number of studies in the past number of years. Han *et al.* [16] have analyzed the probability of extending the battery life cycle and optimizing the battery usage by installing used battery packs in buildings' microgrids. Yilmaz and Krein [17] have formulated a multiobjective optimization problem to minimize the energy storage system size and maximizing the battery cycle life. In [18], the authors have developed an approach to minimize the cost of vehicle battery charging with variable electricity costs while considering the estimated battery degradation costs using a simplified lithium-ion battery lifetime model. A dynamic model of Li-ion batteries incorporating electrothermal and ageing aspects for V2G applications has been presented in [19].

In Luo *et al.* [20] have developed a stochastic framework to enhance the predictability of wind power using EVs through fuzzy c-means clustering. They have used a genetic algorithm with a Monte Carlo simulation to

TABLE 1. Summary of notations.

i	Index of charge/discharge cycle number
t, T	Index and set of charging period time slots
j	Index of EV battery cycle life count
in, *fn*	Initial and final
ε	EV battery available energy (kW.h)
D	Depth of discharge (%)
ε_{DV}	Daily energy consumption in driving (kW.h)
ε_{VG}	Daily energy discharge via V2G (kW.h)
M_w	Mean daily battery wear
s_f	Scaling factor of battery wear during driving
C_c	Capital cost of the battery ($)
C_d	Charge duration of the EV
M_c	Mean daily battery cost ($)
R_{dr}	Equivalent discount rate (%)
SLV	Salvage value of the battery ($)
C_L	EV battery cycle life (cycles)
κ_D	Discharge coefficient at specific D
κ_w	Global wear coefficient
$N_{AC(D)}$	Achievable cycle count at specific D (cycles)
Δt	Time slot duration (hour)
P^{chg}	Charging power (kW)
P^{dchg}	Discharging power (kW)
e	Electricity price ($/kW.h)
f	Frequency regulation price ($/kW.h)
r	Discharge reward under feed-in-tariff policy ($/kW.h)
η^{chg}, η^{dchg}	Charging/discharging efficiencies (%)
$\sigma^{chg}, \sigma^{dchg}$	Charge/discharge binary indicators
wp_r	Wear price of EV battery ($/kW.h)
ϕ	Decay coefficient
S^{ini}	Initial state of charge of the battery (%)
S^{des}	Final state of charge of the battery (%)
γ	Exponential component
$\alpha, \beta, \delta, \omega$	Smoothing parameters
T	Trend component
p	Period of the seasonality
S	First seasonality
I	Second seasonality
$\widehat{X}$	Forecast

optimize charging and discharging, and minimize the sum of the penalty cost associated with wind power imbalances and EV expenses associated with purchased energy, battery wear, and capital costs. In [21], a semi-empirical battery wear model has been proposed for an EV charging based on experimental cycle life data provided by the manufacturer. An auction-based energy trading model among EVs with consideration of practical battery wear has been proposed in [22]. In Jónsson *et al.* [23] have identified the relationships between customer and system operator interests by using an augmented epsilon-constrain based technique to implement multi-objective optimizations. A stochastic methodology for smart charging of EVs has been presented in [24] by considering the impact of charging/discharging strategies on the battery pack degradation. In [25], the authors have formulated a problem for determining the aggregator's bid to indicate its available capacity for frequency regulation in the next day using stochastic programming. Although the authors consider a day ahead pricing for frequency regulation, they do not consider the impact on the end user and the effects of this process on the degradation cost.

Zhou *et al.* [26] have developed charging control strategies while varying the regulation price, charging cost and the desired SOC. Winters [27] have simulated about 250 EVs in the New England regulation services market. Based on their calculations, an EV owner can earn between $1250 and $1400 per year by providing regulation up and down services which result in 9-11% reduction in ownership costs. Taylor [28] have developed a predictive model for charging and regulation to schedule the charging and regulation by using different experiments to support regulation. The authors have considered the problem of an aggregator in minimizing the cost of EVs participating in the regulation process as well as the battery level at plug out. The problem of the aggregator is that it does not know when a new vehicle will arrive for regulation service provision.

Han *et al.* [29] have modelled the regulation data to determine the battery degradation due to V2G participation. They have estimated the power transferred and compared the profit to the cost of degradation. They have used regulation data to determine the cost of degradation while providing the V2G service in comparison to the normal driving situation. However, the authors have not presented or discussed the cycle life profile after each V2G operation. Luo *et al.* [30] have presented a model to estimate the battery degradation based on the results obtained from simulation models while comparing normal driving instances to V2G scenarios. The authors, however, did not show an illustration of the cycle life degradation for EVs providing the V2G operation. They have presented a cost-benefit analysis, but there was no emphasis on the EVs' battery SOC or charge/discharge pattern.

David and Al-Anbagi [3] have presented degradation analysis using a semi-logarithmic model and then compared the results with the battery's C_L experimental results. The authors have estimated the cost of degradation, battery C_L, the amount of power an EV can contribute to the grid while considering daily driving as well as the revenue generated based on the contracted power capacity. The results presented show that EVs can provide the needed frequency regulation service and still make a profit from the activity. However, the analysis did not show the battery cycle life pattern after each V2G operation. In addition, the authors did not discuss the SOC profile and charge/discharge patterns of the EVs participating in the regulation service.

Farzin *et al.* [31] have modelled the degradation cost of EV batteries to calculate the wear price. They have also considered the degradation of the EVs' batteries in V2G programs and developed an optimization model to minimize the battery wear cost of EV batteries participating in the operation. The authors considered only the electricity prices in their optimization, unlike electricity and regulation prices that are considered in this paper to obtain the results and perform the analysis of the SOC profile, charge/discharge patterns for the EVs.

Lepojevic and Andelkovic-Pesic [32] have used Holt Winter (HW) forecasting model to predict electricity consumption while Jónsson *et al.* [33] have predicted the expected imbalance cost in the real-time market using the HW method with daily seasonal cycle. Lepojevic and Andelkovic-Pesic [32], Jónsson *et al.* [33] have not implemented the model to predict frequency regulation prices nor discussed the model for the V2G environment. In this paper, the double seasonal data is considered, unlike the daily seasonal cycle in the HW model. In this paper, the modified HW model is used to fit the specific V2G environment.

It is evident that previous work does not consider the impact of predicted electricity prices and frequency regulation signals on the battery cycle life and on the long-term EV charge/discharge scheduling and planning. In contrast with previous work, in this paper, we present an optimization model based on [4] that incorporates the predicted prices from a forecast model and the charge scheduling problem with the application of the wear cost of the EV batteries. We present the impact of the predicted prices on the optimization model after continuous charge/discharge cycles. We also analyze the hourly SOC profile over the charging period of the EVs and the optimal charge/discharge schedule in the base case with the predicted values.

III. THE EV CHARGE/DISCHARGE MODEL

A. OPTIMAL EV CHARGE/DISCHARGE SCHEDULING MODEL FORMULATION

We develop the optimization model based on [31] and then integrate the battery degradation cost in the charge/discharge scheduling of the EVs. In this paper, we include the frequency regulation price signals and consider several factors in battery degradation to formulate our model. We consider the charge and discharge rates, operational temperature, depth of discharge (D), SOC, end of charge voltage ($EOCV$) and the cycle number.

Based on these additional factors, the loss of cycle life is obtained using the following equation [31]:

$$\Delta\varepsilon_i = \varepsilon_i - \varepsilon_{i+1} = \kappa_D(2\varepsilon_i D) \tag{1}$$

ε_i represents the battery's available energy at the beginning of *ith* charge/discharge cycle. We introduce κ_D to account for the variable loss of cycle life at different SOCs.

The available energy at an arbitrary cycle (ε_n), is represented in terms of the initial rated energy ε_0 using the following equation [31]:

$$\varepsilon_n = \varepsilon_0(1 - 2\kappa_D D)^n \tag{2}$$

After going through certain cycles, the available battery energy will decrease to 80% of ε_0 based on the achievable cycle count (AC) and D characteristic [34]. Therefore, the value of κ_D can be found using the following relation:

$$\kappa_D = \frac{1}{2D}(1 - 0.8^{\frac{1}{N_{AC(D)}}}) \tag{3}$$

We can obtain the loss of available energy caused by charging or discharging processes between two given SOCs by using the following equation:

$$\Delta\varepsilon = \varepsilon|D_{in}\kappa_{D_{in}} - D_{fn}\kappa_{D_{fn}}| \tag{4}$$

where D_{in} is is the initial depth of discharge. Equation (4) can be approximated as follows:

$$\Delta\varepsilon = \kappa_w\varepsilon|D_{fn} - D_{in}| = \kappa_w\varepsilon|D_{in} - D_{fn}| \tag{5}$$

where, $D_f n$ represents the initial and final depth of discharges respectively.

We calculate the mean daily battery wear (M_w) using the following equation:

$$Mw = \kappa_w((1 + s_f)\varepsilon_D V + 2\varepsilon_V G) \tag{6}$$

As a result of more rapid cycling, s_f accounts for the scaling factor of battery wear during driving (i.e. the higher capacity loss during the driving mode operation compared to that of the V2G).

The battery cycle life can be evaluated using the following equation:

$$C_L = \frac{0.2\varepsilon_0}{M_w} \tag{7}$$

We calculate the daily wear cost (Mc) by modelling the degradation cost as a series of equal payments during the estimated cycle life. We do this based on engineering economic principles and is given by:

$$Mc = \frac{R_{dr}(C_c(1 + R_{dr})^{C_L} - SLV)}{(1 + R_{dr})^{C_L} - 1} \tag{8}$$

The wear price (wp_r) is defined as the cost of battery degradation associated with 1 kWh of processed energy and can be calculated using the following equation:

$$wp_r = \frac{M_c}{(M_w/\kappa_w)} \tag{9}$$

It is important to note that the battery specifications are obtained from [34], a ratio of 60 is considered for SLV/C_c, and the annual discount rate is 5%.

B. FREQUENCY REGULATION PRICE ANALYSIS

Frequency regulation price can be defined as the market price for regulation services which is provided by the ancillary market. It includes the price for regulation up or down and is influenced by several factors including the load demand in response to automated signals at a specific time.

In this paper, we consider the New York Independent System Operator (NYISO) [35] which determines regulation prices based on the demand for the regulation service. In the NYISO regulation market, resources may submit bids for regulation reserves until the real-time market closes. Several suppliers include different response rates that can be achieved after which NYISO sets the regulation prices [36]. The hourly tariff considered is the Locational Marginal Pricing (LMP) [35] while the New York Control Area (NYCA) regulation capacity is used for the regulation price [35]. We only use the NYISO LMP and NYCA regulation price for our optimization model. We use hourly time step because the jurisdiction considered in this paper (NYISO) has electricity and frequency regulation prices in hourly timestamps. Other jurisdictions with lower time steps can also be considered as well. It is imperative to note that the charging/discharging power of the EV batteries is dependent on the combination of the electricity and frequency regulation prices in the optimization model.

C. EV CHARGE/DISCHARGE SCHEDULING PROBLEM WITH WEAR COST AND REGULATION SIGNAL

We briefly describe the development of the modified model, the interested reader is referred to [31] for more details. The modifications include the incorporation of the actual regulation signals in the objective function. We do this and show the impact of these signals on the optimal SOC profile and charge/discharge cycle while considering the wear cost as follows:

$$\begin{aligned} \text{Minimize } & \sum_{t=t_b}^{t_e} \Delta t\Big(\big(P_t^{chg}(e_t+f_t) - P_t^{dchg} r_t\big) \\ & + \big(P_t^{chg}\eta^{chg} + P_t^{dchg}/\eta^{dchg}\big) wp_r\Big) \quad (10) \end{aligned}$$

$$\begin{aligned} \text{subject to: } & 0 \le P_t^{chg} \le \sigma_t^{chg} P_t^{chg.max}, \\ & \sigma_t^{chg} \in (0,1), \quad \forall t \in T \quad (11) \\ & 0 \le P_t^{dchg} \le \sigma_t^{dchg} P_t^{dchg.max}, \\ & \sigma_t^{dchg} \in (0,1), \quad \forall t \in T \quad (12) \\ & S^{min} \le S_t \le S^{max}, \quad \forall t \in T \quad (13) \\ & \sigma_t^{chg} + \sigma_t^{dchg} = 1, \quad \forall t \in T \quad (14) \\ & S_{t+1} = S_t \\ & \quad + (P_t^{chg}\eta^{chg} - P_t^{dchg}/\eta^{dchg})\Delta t, \quad \forall t \in T \quad (15) \\ & S_{t_b} = S^{ini} \quad (16) \\ & S_{t_e} = S^{des} \quad (17) \end{aligned}$$

The objective function in (10) is a Mixed Integer Linear Programming (MILP) problem. The first term of equation (10) represents the LMP (electricity and frequency regulation price) for the battery charging and ancillary service provision. The second term represents the discharging power reward paid to the customers according to the feed-in-tariff policy. The third and fourth terms represent the degradation cost. We reemphasize that both charge and discharge processes lead to battery wear. Therefore, after considering the charging and discharging efficiencies, the wear contributions are represented in (10). To do that, we use a constant wear price value. Both terms of equation (10) are multiplied by a single time slot duration (e.g. 1 hour) and then integrated over the entire charging time T to obtain the total charging cost. The values of (P_t^{chg}, P_t^{dchg}, σ^{chg}, σ^{dchg} *and* S_t) in the optimization model are obtained for different time slots so that the total charging cost and frequency regulation price specified in equation (10) are minimized.

The allowable charging and discharging power limits (representing the constraints) of the EVs are specified in equations (11) and (12) respectively. Equation (13) defines the allowable SOC operational range limit. Equation (14) is used to prevent simultaneous charging and discharging. Equation (15) represents the relationship between the charging/discharging power and SOC. Equations (16) and (17) represent the SOC at the beginning of the charging period and the desired value (100%) after completing the charging process.

IV. DOUBLE SEASONAL HOLT WINTER MODEL

The HW model is also known as triple exponential smoothing. It is a way to model and predict the behavior of a sequence of values over time (time series). HW is one of the most popular forecasting techniques for time series. HW model is a way to model three aspects of the time series: level (average), trend (slope) and seasonality (pattern). It uses exponential smoothing to encode many values from the past and use them to predict or forecast values for the present and future. The model predicts a current or future value by computing the combined effects of the aspects of the model.

The Double Seasonal Holt Winter (DSHW) model is a modification of the standard HW model described in [37] and [38] . In this paper, we consider the standard HW model to compare its accuracy with the DSHW model. We use the DSHW model because the historical prices data from NYISO (August 1st, 2017 to August 31st, 2017) has a double seasonal pattern. We apply this method to a series of hourly demand where we set $p_1 = 24$ and $p_2 = 168$. The DSHW model with double seasonality pattern is described as follows, [38]:

$$\begin{aligned} \gamma_t &= \alpha\big(X_t/(S_{t-p_1} I_{t-p_2})\big) + (1-\alpha)(\gamma_{t-1} + T_{t-1}) \quad (18) \\ T_t &= \beta(\gamma_t - \gamma_{t-1}) + (1-\beta)T_{t-1} \quad (19) \\ S_t &= \delta\big(X_t/(\gamma_t I_{t-p_2})\big) + (1-\delta)S_{t-p_1} \quad (20) \\ I_t &= \omega\big(X_t/(\gamma_t S_{t-p_1})\big) + (1-\omega)I_{t-p_2} \quad (21) \\ \widehat{X}_t(k) &= (\gamma_t + kT_t)S_{t-p_1+k} I_{t-p_2+k} \quad (22) \end{aligned}$$

We implement the DSHW model to predict the electricity and frequency regulation prices for one month in NYISO. We compare the actual (i.e. real) NYISO and the predicted electricity and frequency regulation prices. Fig. 1 and Fig. 2 show the implementation results of the DSHW model for the period from August 1st to August 31st, 2017. We show that the predicted electricity and frequency regulation prices are close during the simulation period. We perform a more detailed analysis by testing the accuracy of the DSHW model. MAE is the mean absolute error between the actual (real) prices and the predicted prices. The values show that the accuracy of the forecast model is high as the predicted electricity and regulation prices are close to the real prices. MAPE is related to MAE but in this case, it is the mean absolute percentage error. The values show a good agreement between the actual values and the forecast values obtained from the DSHW model. MASE, on the other hand, is the mean absolute scaled error, where the DSHW gives MASE values for

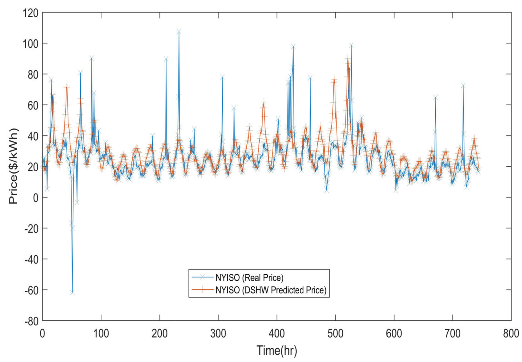

FIGURE 1. One month NYISO DSHW model predicted and real electricity prices.

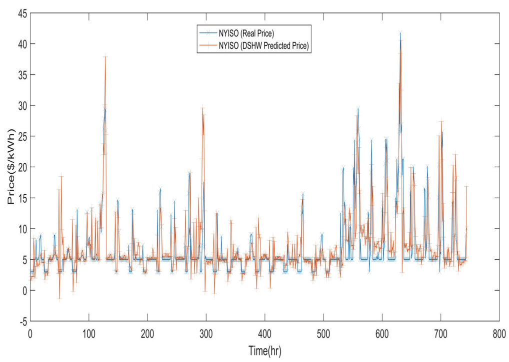

FIGURE 2. One month NYISO DSHW model predicted and real frequency regulation prices.

TABLE 2. Statistical parameters for evaluating forecast accuracy of DSHW model.

Accuracy Measure	Electricity Price	Regulation Price
MAE	1.95	5.07
MAPE (%)	18.59	32.96
MASE	0.459	0.644
MSE	10.71	11.50
RMSE	3.27	3.39

electricity and regulation prices to be less than 1 which means the model is more accurate when compared to a simple forecast. MSE and RMSE are the mean squared error and root mean squared error respectively. The low values for both electricity and regulation prices show the DSHW has a high degree of accuracy. Table 2 shows the statistical parameters for evaluating the forecast accuracy of the DSHW model.

Table 3 shows the statistical parameters for evaluating the forecast accuracy of the HW model. We see from Table 3 that the model does not have a good accuracy because the data considered is double seasonal and the HW model cannot predict well under these conditions. This is because the HW model uses the same seasonality for the entire month while the DSHW model uses daily and weekly seasonality to predict the prices for the next month. Due to these inaccuracies,

TABLE 3. Statistical parameters for evaluating forecast accuracy of HW model.

Accuracy Measure	Electricity Price	Regulation Price
MAE	9.82	20.04
MAPE (%)	53.45	482
MASE	0.76	2.64
MSE	12.09	23.41
RMSE	12.09	23.41

in the reminder of this paper we follow the DSHW model to obtain the results.

V. EVCD OPTIMIZATION WITH DYNAMIC CYCLE LIFE

A. CYCLE LIFE

C_L is dependent on battery degradation which is the amount and rate of energy used up in a battery. It is also a function of the D and cycle frequency which indicates the number of charge-discharge cycles an EV battery can undergo before it drops below a certain level. Typically, the nominal level for degradation is said to be 80% D which is the recommended regime to be utilized for a Li-ion battery [3]. According to [3], the C_L of the battery is given by:

$$C_L = (L_{100})e^{\phi(1-D)} \tag{23}$$

where C_L is the cycle life of a battery, L_{100} is the value of the C_L at 100% D and ϕ is the decay coefficient. Decay coefficient is the exponential decrease in the value of the cycle count and its value falls between 3 and 6 for different batteries [3].

B. THE ITERATIVE FRAMEWORK WITH DYNAMIC CYCLE LIFE

Algorithm 1 shows the proposed iterative algorithm for estimating the C_L. The initial battery C_L is initialized with the corresponding value of D. We obtain the electricity and regulation prices from the NYISO website. We simulate the EVCD optimization model to obtain the optimal charge/discharge patterns.

After one iteration, we obtain the charge/discharge patterns and the SOC profile are based on the optimization model and the cycle loss after the operation is recorded. We then verify the corresponding D for the obtained cycle loss with the values preset by the EV owner. We do that to maintain the C_L within operational range. Therefore, as long as the set D limit is not reached, the iterations continue for the next charge/discharge cycles. The charge/discharge process stops and the operation is terminated when the C_L is below the operational level. As stated above, we use the historical data from NYISO to set the maximum and minimum price ranges for our model. We also set the value of E_{V2G} according to the total discharged energy in the optimal solution. The cycle life count obtained from the iterative algorithm gives the EV owner an insight on the loss count of the EV battery, decision whether or not to participate in future frequency regulation

Algorithm 1 Iterative Algorithm for EVCD Optimization With Dynamic Cycle Life

Initialize: ε_{VG}, ε_{DV}, ε_0, K_{adr}, K_w, s_f, C_{in}, R_{dr}, C_d
Input: ε_0
$s_f = 128 * \varepsilon_0$
Output: s_f
Input: s_f
SLV = 0.60 * s_f
Output: SLV
for *D = 100% to 0%* **do**
  Initialize j = 0, C_{new} = 0, $C_L = C_{in}$
  while *% Change in C ≥ D* **do**
    Input: K_w, s_f, ε_{DV}, ε_{VG}
    $M_w \leftarrow$ equation (6)
    Output: M_w
    Input: R_{dr}, C_c, SLV, C_L
    $M_c \leftarrow$ equation (8)
    Output: M_c
    Input: M_c, M_w, K_w
    $wp_r \leftarrow$ equation (9)
    Output: wp_r
    Input: wp_r, e_t, f_t
    Minimize wear cost from $\leftarrow$ equation (10)
    subject to $\leftarrow$ from equations (11) to (17)
    % Change in D = (C_j - C_{new}) / C_{in}
    Increment j,
    $\varepsilon_{VG_j} = \varepsilon_{VG_{new}}$
    $e_t, f_t = (e_{t_j}, f_{t_j})$ + Gaussian normal ($\mu = 0$, σ = 0.01)
  end
  Output j
end
Output D

service provision and the EV battery depth of discharge after each charge/discharge operation.

VI. RESULTS AND ANALYSIS

As previously discussed, we focus on the impact of frequency regulation signals on the cost of providing V2G services. We briefly describe how we obtained different frequency regulation price signals for the EV charge scheduling optimization model and how the frequency regulation signals interact with the optimization model. We focus on the minimization of the battery degradation cost to obtain our results and perform our analysis. We present a charge scheduling scenario of EVs considering an electricity pricing model (hourly pricing) using the case study in [4]. The charging period of the EV starts at 18:00 and the vehicle remains connected to the power grid for a period of 14 consecutive hours (until 6:00). The battery capacity is 29.07 kWh [31] and the average daily energy used in driving is 8. 72 kWh [31] which corresponds to an average value of 70% for SOC at the beginning of the charging period. We assume that the charging and discharging efficiencies are 93% [31]. We use the hourly electricity prices, frequency regulation prices for NYISO, and the predicted electricity and frequency regulation price from the DSHW model to show the comparison between the SOC profile and charge/discharge patterns. We assume that the reward for the feed-in-tariff policy of the discharged energy by the EVs is 0.3 US$/kWh [31]. We assume that the final desired SOC for the base case is equal to 100%. We analyze the effect of static and dynamic electricity and regulation prices on the cycle life of the battery. We consider three cases for the maximum charge and discharge powers (level 1 charging: 2.3 kW, level 2 charging: 7.4 kW, and fast charging: 22 kW) and discuss how these powers affects the results.

TABLE 4. Simulation parameters.

Parameter	Value/Comments
Δt	1 hr
P_t^{chg}	0.00 - 2.30 kW/ 7.4 kW/ 22 kW
P_t^{dchg}	0.00 - 2.30 kW/ 7.4 kW/ 22 kW
e_t	Obtained from Fig. 3.
f_t	Obtained from Fig. 3.
r_t	0.30 $/kW.h
η^{chg}, η^{dchg}	0.93
$\sigma^{chg}, \sigma^{dchg}$	0 or 1
wp_r	0.0868
S^{ini}	70%
S^{des}	100%

We assume that the number of EVs used in our case study is one because the idea is to see how an EV charging/discharging can be optimized to perform frequency regulation with minimal wear cost and battery degradation. Multiple EVs can be considered as well although the impact/assessment is still for each individual EV. Studying the impact of multiples EVs is however beyond the scope of this paper.

Our case study focuses on the impacts of frequency regulation prices, the SOC profile, and the charge/discharge pattern on battery degradation. We assume that the type of frequency regulation does not impact the optimization model since the aggregators manage the charging/discharging through an aggregated power (independent of primary or secondary regulation). EVs charge/discharge optimization to achieve primary or secondary regulation is out of the scope of this paper. Table IV. shows the simulation parameters used to obtain our results.

Fig. 3. shows the NYISO hourly real and DSHW predicted tariff and regulation price which is fed into the EVCD optimization model. The frequency regulation price is the impact of the frequency regulation signals which shows the behavioural pattern of the EVs. We show that the regulation price is low between 1:00 to 2:00 thus EVs prefer to charge or remain idle over performing regulation. From 3:00 to 6:00 when the prices are high, the EVs would likely discharge power to provide regulation. When prices drop again from 7:00 to 9:00, EVs can decide to charge again. From about

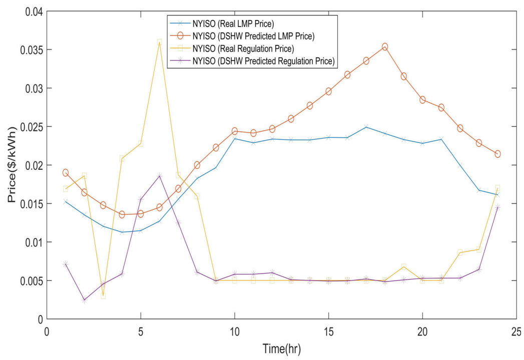

FIGURE 3. NYISO (Real and DSHW predicted price).

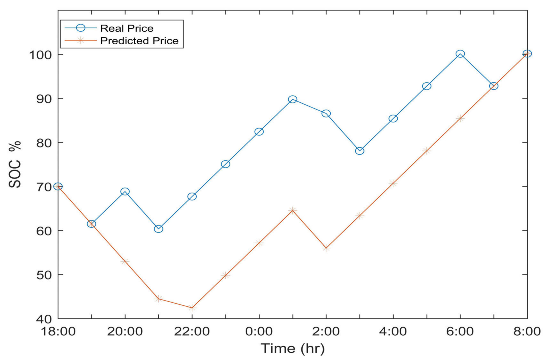

FIGURE 4. SOC profile for 2.3 kW power and NYISO hourly pricing.

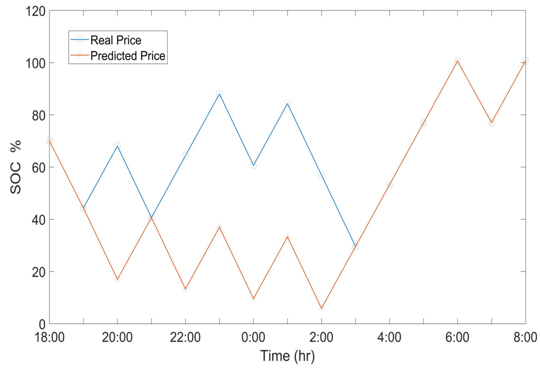

FIGURE 5. SOC profile for 7.4 kW power and NYISO hourly pricing.

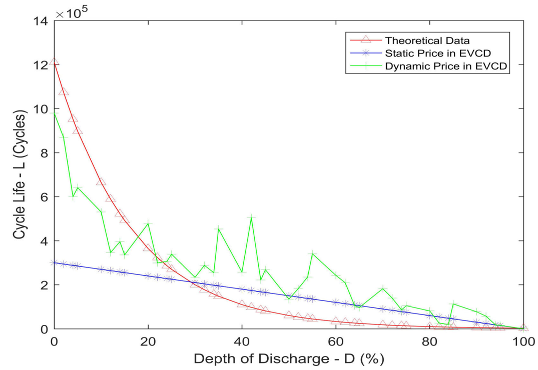

FIGURE 6. SOC profile for 22 kW power and NYISO hourly pricing.

10:00 to 22:00, the regulation price is low for a period of time, EVs might continue to either charge or discharge their batteries or remain idle for the next ancillary service provision. Finally, the EVs would charge from about 23:00 to 24:00 to satisfy the desired final SOC regardless of the regulation price (although high in this case). We next simulate a combination of both electricity and regulation prices into the EVCD model.

Fig. 4. shows the hourly SOC profile for both the real and predicted prices for 2.3 kW charging and discharging power. For the real price, it is seen that from 18:00 to 19:00, the EVs discharge due to the slight increase in the prices (combined electricity and regulation price) compared to the previous hours. The EVs charge from 19:00 to 20:00 when the price is low but discharge again from 20:00 to 21:00 due to a change in the prices. From 21:00 to 1:00, the EVs charge their batteries and are available to provide regulation down requests from the grid operator. A drop in the tariff from 1:00 to 3:00, allows the EVs to discharge to support the regulation up services. Between 3:00 and 6:00, the EVs charge and offer to provide the regulation down services again. From 6:00 to 7:00, the EVs discharge to provide regulation services. Finally, from 7:00 to 8:00, the EVs charge their batteries to 100% based on the constraint of the EVCD model.

For the DSHW predicted prices, the SOC profile is shown in Fig. 4. The EVs discharge their batteries from 18:00 to 22:00 due to the high tariff of the combined prices (electricity and regulation price) and in a bid to offer regulation up service requests. From 22:00 to 1:00, the EVs begin to charge since the tariff is quite low and regulation down services can be provided. The price increases from 1:00 to 2:00, thus the EVs discharge to satisfy the regulation up request from the grid operator. Finally, the EVs charge from 3:00 to 8:00 due to the low tariff of the combined prices and in order to offer regulation down requests. It is important to note the changes in the SOC are determined simulation from the EVCD optimization. It is also worth noting that the EVs charge to 100% based on the constraint of the EVCD optimization model as the desired SOC on completion of the regulation service. The difference in the SOC profile graphs is based on the fluctuations (increase/decrease) in electricity and regulation prices, the power level of the EV battery and the optimization done by the EVCD model. Fig. 5 and Fig. 6 show the hourly SOC profile for both the real and predicted prices for 7.4 kW and 22 kW charging and discharging power respectively. Figures 5 and 6 follow a similar trend to that of Fig. 4 but with different charging/discharging rates and patterns.

Fig. 7 shows the optimal charge/discharge schedule for both the real and predicted prices and 2.3 kW charging and discharging power. For the real price, Fig. 7 shows the EVs discharge their batteries with maximum power from 18:00 to 19:00. From 19:00 to 20:00, the EVs charge with maximum power. The EVs discharge again with maximum power from 20:00 to 21:00 when the price for providing the regulation

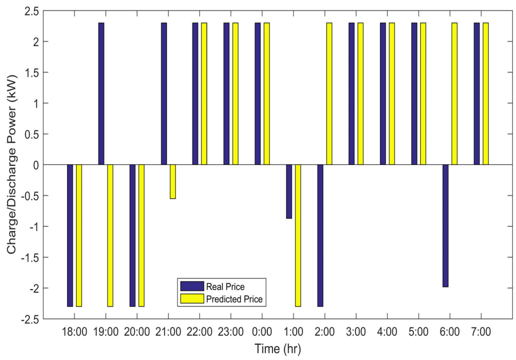

FIGURE 7. Optimal charge/discharge schedule for for 2.3 kW power and NYISO hourly pricing.

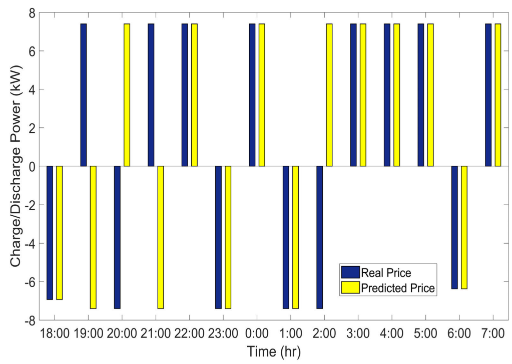

FIGURE 8. Optimal charge/discharge schedule for 7.4 kW power and NYISO hourly pricing.

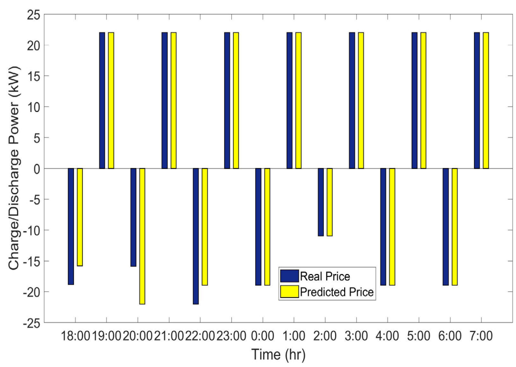

FIGURE 9. Optimal charge/discharge schedule for for 22 kW power and NYISO hourly pricing.

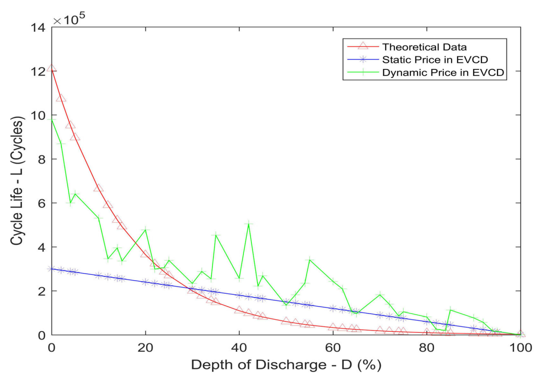

FIGURE 10. Dynamic cycle life for Li-ion battery after V2G operation.

service is high. From 21:00 to 0:00, the EVs charge with maximum power to provide regulation down services. The EVs discharge but with minimal power (around 40% of the maximum power) from 1:00 to 2:00. From 2:00 to 3:00, the EVs discharge with maximum power due to the high price for offering the regulation service. Between 3:00 and 5:00, the EVs charge with maximum power and from 6:00 to 7:00, they discharge to about 85% (2.0 kW) of the maximum power because the price for regulation up service is not as high as previous hours of regulation up service. Finally, the EVs charge to 100% with maximum power to fulfill the desired SOC as simulated by the EVCD optimization. For the DSHW predicted price, the EVs discharge to a minimum power level from 18:00 to 20:00. At 21:00, the EVs discharge to minimal power based on the electricity and regulation prices during this hour simulated in the optimization model. This period could also be termed as a conservative period because the EV can decide to remain idle or charge/discharge based on the EVCD optimization. From 22:00 to 0:00, the EVs charge to maximum power, where we see the EVs charge their batteries to a maximum at 0:00 to ensure there is sufficient power for the regulation down service since the revenue to be generated is increased as simulated by the optimization model. At 1:00, the EVs discharge with maximum power due to the increased price of electricity and regulation to participate in regulation up service compared to the previous hour. From 2:00 to 8:00, the EVs constantly charge because of the low tariff of the combined prices thus the EVs provide regulation down services. The differences in graphs are visible because the predicted price is the result from the forecasting model and there is a minimal discrepancy between the values. The variations in the combined prices result in a slight change in the SOC profile and charge/discharge patterns of the EV. As mentioned earlier, the predicted price provides the EV control system information on the future SOC profile, charge/discharge patterns. Fig. 8 and Fig. 9 show the optimal charge/discharge schedule for both the real and predicted prices for 7.4 kW and 22 kW charging and discharging powers respectively. Figures 8 and 9 follow a similar trend to that of Fig. 7 but with different charging/discharging rates and patterns.

Fig. 10. shows the battery's dynamic cycle life after an extended charge/discharge operation. The results show an exponential trend related to the theoretical data obtained from (23) and show a linear trend from the EVCD model when the electricity and the regulation prices are assumed to be static. For the dynamic prices, the highly variable line shows the impact of the electricity and regulation prices on the cycle life. It is seen that when D is equal to 0% the cycle life remains at a high value (i.e. charge/discharge processes has started yet). However, when the charge/discharge processes start (from 1% through 100%), the cycle life gradually decrease. However, the rate is dependent on the previously

mentioned prices simulated by the EVCD model. The results in Fig. 6 give the EV owner an idea about the extent at which the battery can perform for long-term charge/discharge operations.

To show the effects of the predicted prices on the battery cycle life count, we notice that there is not sufficient input for the iterative algorithm giving the entries shown in Fig. 1. and Fig. 2. It is important to note that for the iterative algorithm to produce the desired results and predict the cycle life count, it would need much more predictive data for years. Based on our knowledge, there is no model that can predict electricity and regulation data for that duration. Therefore, we rely on the previously explained theoretical (static) and random variable (dynamic) price incorporated into the EVCD model for the EV battery cycle life estimate.

VII. CONCLUSION

In this paper, we developed and evaluated a model to minimize the wear cost of EV battery when EVs are used to support the frequency regulation service. We presented an iterative algorithm to find the loss in cycle life when the batteries undergo certain charge/discharge cycles. Furthermore, We included actual frequency regulation signals and the results from the DSHW model into our EVCD model to achieve the desired results. We performed our analysis based on a realistic case study which uses actual prices. We presented the SOC profile, charge/discharge patterns for both the real and predicted (electricity and regulation) prices. Finally, We presented the cycle life count after each V2G operation compared between the theoretical, experimental and simulated data. Our results and analysis showed that EV owners can effectively participate in frequency regulation services and generate a revenue while minimizing the battery degradation cost.

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