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Stochastic approach to minimize the cost of electricity for depot operator with constrained grid supply

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ABSTRACT Electrification of local transport will be challenging for the depot operators located in high density areas with constrained power supply from grid. This paper proposes an energy management framework to minimize the cost of electricity for the depot operator by optimal charge-discharge scheduling of electric buses while utilizing the batteries installed in electric buses. A mixed-integer linear programming based stochastic optimization technique is used for optimal charge-discharge scheduling of energy storage units. The proposed framework estimates the capacity of stationary energy storage unit in the first stage to mitigate the demand and supply gap due to constrained grid power supply. It then bids conservatively in the day-ahead energy market while exploiting the favourable costs of both energy markets i.e. day-ahead and real-time, based on large number of potential scenarios. The proposed framework also accounts for capacity degradation of the energy storage units due to charging-discharging power capacity as well as repeated charge-discharge cycles. The efficacy of the proposed framework is validated using case studies considering a hypothetical bus depot in Australia. Comparison with the state-of-the-art scheduling strategies show that the proposed framework can provide overall cost savings of 34% compared to uncoordinated scheduling and 23% compared to deterministic scheduling strategy.

INDEX TERMS Energy Management Framework, Electric Bus, Mixed-Integer Linear Programming, Optimization, Depot Operator, Battery Sizing

I. INTRODUCTION

ONE quarter of the global green house gas emissions are caused by transportation sector and these emissions are continuously increasing compared to any other energy sector [1]. The energy consumption in transport sector has been increasing for past four consecutive years and has reached a new record high (1,251 Mtoe), confirming its position as the largest energy consuming sector [2]. High fuel consumption and consequent emission production can be mitigated by electrification of the transport sector. Transport electrification is on the rise due to favorable regulations and technological advancements. As of 2019, there are more than 400,000 electric buses on the road in China alone, being the largest market for electric buses in the world accounting for almost 99% of the world total [3].

However, the electrification of large fleets of buses will have significant impact on the electric grid. The uncoordinated charging of electric buses can result in tremendous impact on the peak demand of the local electricity network [4]. The increasing energy demand could either be mitigated with network fortification or by demand side management (DSM). Enhancement in the network requires high cost investment which will have to be paid by the electricity consumers eventually. The DSM can help in extending the limits of the grid further without extraordinary cost investments [5]. However, the costs involved in the DSM strategies does require investments in terms of incentivizing the consumers in return for compromising their freedom in some cases for using the utilities at will.

Bus depot being the aggregated charging hub for the electric buses, will play a significant role in managing the electrical load profile for the grid by optimal charge-discharge scheduling of electric buses. The depot operators with an on-site distributed energy resource (DER) generation, are anticipated to increase due to advancements in storage technologies and complimentary regulations. These advances in technology and complimentary regulations along with the evolving transactive energy markets will allow significant cost reduction opportunities for the depot operators. Specifically, the depots with vehicle-to-grid (V2G) operational functionalities enabled will play a key role in optimally utilizing the offered incentives by the transactive energy market. Therefore, an energy management framework capable of effective load scheduling & resource management strategies, will offer remarkable savings in cost for the depot operator [6], [7].

II. LITERATURE REVIEW

To the best of author's knowledge, little research endeavors have been made towards developing an efficient energy management system for charge-discharge scheduling of electric buses. Even fewer researches have explored the domain of bi-directional electricity trading to minimize the cost of electricity for the depot operators. Existing research in managing the electric bus charging-discharging operations mainly focuses on minimizing the cost or managing the peak load demand.

Most of the existing literature dealt with energy management problems by minimizing the cost of electricity. As optimal scheduling of electric vehicles including electric buses, is proposed in [8] where parking lot operators participate in energy, reserve and regulation distribution markets to minimize cost. Authors in [9] proposed a charge scheduling algorithm for maximizing the profit for the electric bus depot operator while considering grid stability constraints. Considering the charging schedule of electric buses for the depot, the authors in [10] tested a model on a fleet of 10 buses which takes the time-of-use tariff to minimize the cost of energy. An optimization model for minimizing cost of fast charging infrastructure and also battery capacity sizing of the electric bus is proposed by authors in [11]. A cost-minimization model to determine the deployment of electric bus charging stations and a grid connection scheme was proposed in [12]. An optimal scheduling method based on dynamic programming was proposed by authors in [13], to minimize battery replacement costs during the entire service life of electric bus fleets. An electric bus power consumption model and optimization of charge scheduling while considering multiple external factors is proposed by authors in [14] to maximize profit. An optimal charging schedule scheme in a wirelessly charged electric bus system has been explored in [15] to minimize the electricity cost. An optimization method, for the electric vehicle scheduling with multiple vehicle types including electric buses to minimize cost, is proposed by authors in [16].

Some studies used peak load management as the objective function for managing energy of electric bus fleets. As algorithms for charge scheduling of electric buses were proposed in [17] to minimize the peak load. Multi-objective algorithms for managing the charging of the fleet of electric buses were proposed in [18] to minimize energy consumption, peak load demand and ageing of the battery.

The objective of all the studies discussed above is energy management of the electric bus depot by either minimizing the cost and maximizing the profit for the depot operator, or minimizing the peak load. However, none of the studies considered the constrained grid problem, which is most likely to be the case specifically for bus depots located in high density areas where the supply from electric power grid is constrained. This particular type of problem needs generic solutions which would also consider capacity estimation of energy storage units as found missing in [8]–[10], [12]–[18].

The deterministic approach for optimal charge-discharge scheduling of electric buses as considered in [9]–[18] does not account for the uncertainties associated with the stochastic nature of certain variables like the arrival time of buses at the depot, departure time of buses from the depot, the distance travelled by the buses, the efficiency of the buses, fixed site load profiles, on-site distributed energy resource generation and the energy market tariffs.

Energy storage units are subject to capacity degradation due to charging-discharging power [19] and also repeated charging-discharging cycles [20]. Some literature on energy management for electric bus depot does not account for battery capacity due to power capacity as in [9], [10], [12]–[17] while some did not consider capacity degradation due to repeated charging-discharging cycles as in [8]–[12], [14]–[18].

Some of the literature discussed above did not consider vehicle-to-grid flexibilities of the energy storage units installed in the electric buses as in [10], [12]–[18]. Also, some research focused on fast charging solutions at decentralized charging stations, instead of traditional overnight and opportunity charging at the centralized bus depots as in [11], [12], [15].

In summary, existing literature lacks an energy management framework which schedules the optimal charging-discharging of electric buses to minimize the cost of electricity for the centralized depot operator with constrained grid power supply. The framework should be capable of estimating capacity of stationary energy storage unit and also account for the uncertainties associated with the predicted parameters while also accounting for capacity degradation of energy storage units due to charging-discharging power capacity and also repeated charging-discharging cycles by imposing penalty costs.

III. CONTRIBUTIONS

This paper proposes a comprehensive energy management framework which schedules the optimal charging-discharging of electric buses to minimize the cost of electricity for the depot operator with constrained grid power supply, equipped with an on-site distributed energy resource. A mixed-integer linear programming based stochastic optimization technique is used for optimal charge-discharge scheduling of electric buses while accounting for uncertainties associated with the predicted parameters. A modified method for stationary battery capacity selection is presented to mitigate the shortage of power supply from grid. Usual optimal battery sizing models are non-linear and require more computational time for optimal charge-discharge scheduling of energy storage units. However, the proposed method estimates a nominal capacity of stationary battery which is used in the linear optimization model for charge-discharge scheduling of energy storage units with reasonable computation time. The proposed framework also accounts for capacity degradation of energy storage units due to charging-discharging power capacity and also repeated charging-discharging cycles by imposing penalty costs. The key contributions of this paper are:

- A framework for battery sizing and optimal charge-discharge scheduling of electric buses to minimize the cost of electricity for the depot operator with constrained power supply from grid, using mixed-integer linear programming based stochastic optimization approach.
- The modified method for capacity estimation ensures appropriate size calculation of stationary battery, which allows optimal charge-discharge scheduling of energy storage units using linear programming based approach in a reasonable computation time.
- Accounting of energy storage capacity degradation, due to charging-discharging power capacity and repeated charge-discharge cycles, by imposing penalty costs.
- Accounting for uncertainties associated with the predicted parameters using scenario based stochastic optimization approach.

IV. PAPER ORGANIZATION

The paper is organized as follows: the system architecture of the proposed energy management framework is presented in section V, followed by the details of modified battery sizing method in section VI, battery operations modelling in section VII, details of the proposed energy management framework in section VIII, the numerical validation is presented in section IX, results are presented in section X, discussion on the results is presented in section XI, and section XII concludes this paper.

V. SYSTEM ARCHITECTURE

The overview of the system architecture for the proposed EMS is presented in fig. 1. The proposed framework is developed for a depot operator managing electric buses. The power supply at the depot from the grid is constrained and the depot is equipped with on-site solar generation and a stationary battery storage to compensate for the energy shortfall. The key stakeholders of the proposed EMS are the depot operator, grid operator and the energy market operator. It is assumed that the system under consideration is capable of carrying out all necessary information exchanges between the stakeholders.

The depot operator manages the operations of electric buses based on run schedules. The electric buses charge at the depot only with no on-route charging options. The depot operator also exploits the battery storage on the wheels through vehicle-to-building (V2B) or vehicle-to-grid (V2G) flexibilities. The depot operator sends flexible energy bids to the grid operator based on the run schedule of electric buses, on-site solar generation forecasts, stationary battery capacity and the price signal from the energy market. These energy bids are estimated using the proposed EMS which evaluates the optimal charge-discharge schedules for the electric buses to minimize the cost of electricity for the depot operator while managing all the associated system constraints.

VI. BATTERY SIZING

The power supply capacity to the depot is constrained from the grid operator. Therefore, the depot is equipped with an on-site solar generation and a stationary battery to meet the charging demand of electric buses and minimize the cost of electricity for the depot operator. A modified method for battery sizing is proposed in this paper which also accounts for the potential vehicle-to-grid flexibilities of electric buses which is missing in [21].

The proposed model is loaded with the set of hourly load profiles which include aggregated charging demand of electric bus i.e. $\mathcal{P}_t^c$, fixed load i.e. $\mathcal{P}_t^L$, on-site solar generation i.e. $\mathcal{P}_t^K$ and grid capacity constraint i.e. $\overline{\mathcal{P}}$. These parameters are drawn from the historic time-series data. Other non-time dependent input parameters include, upper and lower bounds for state of charge of energy storage units u are i.e. $\overline{\delta}_u \& \underline{\delta}_u$, commercially available stationary battery capacity i.e. $\overline{\chi}_u^{com}$, electric bus battery capacity i.e. $\overline{\chi}_u$ and vehicle-to-grid utilization factor i.e. $\mathcal{F}_{v2g}$.

The potential vehicle-to-grid flexibilities are estimated, which helps in reducing the size of stationary battery to meet the charging demand of electric buses and minimize the cost of electricity for the depot operator. The vehicle-to-grid energy supply i.e. P_t^{v2g} is estimated based on the historic time-series data of electric buses available at the depot with their respective energy states. This estimation is based on eq. (1).

$$P_t^{v2g} = \mathcal{F}_{v2g} \sum_{v=1}^{V} \left(\mathbb{A}_{t,v} \left(\delta_{t,v} - \underline{\delta}_v \right) \overline{\chi}_u \right) \tag{1}$$

here $\mathbb{A}_{t,v}$ is the binary parameter for availability of electric buses $v \in V$ at time $t \in T$ in the depot. $\delta_{t,u}$ represents the state-of-charge of the energy storage units $u \in V, B$, where V is the set of electric buses and B is the set of stationary batteries. $\mathcal{F}_{v2g}$ is the vehicle-to-grid flexibility factor. The gap between supply and demand is calculated using eq. (2)

$$\mathcal{P}_t^{gap} = \underbrace{\left(\mathcal{P}_t^{v(c)} + \mathcal{P}_t^L \right)}_{\text{demand}} - \underbrace{\left(\overline{\mathcal{P}} + \mathcal{P}_t^K + P_t^{v2g} \right)}_{\text{supply}} \tag{2}$$

where $\overline{\mathcal{P}}$ is the grid capacity constraint, $\mathcal{P}_t^c$ is the aggregated charging demand of electric buses, $\mathcal{P}_t^L$ is the fixed load of the depot and $\mathcal{P}_t^K$ is the on-site solar generation. The sum of all

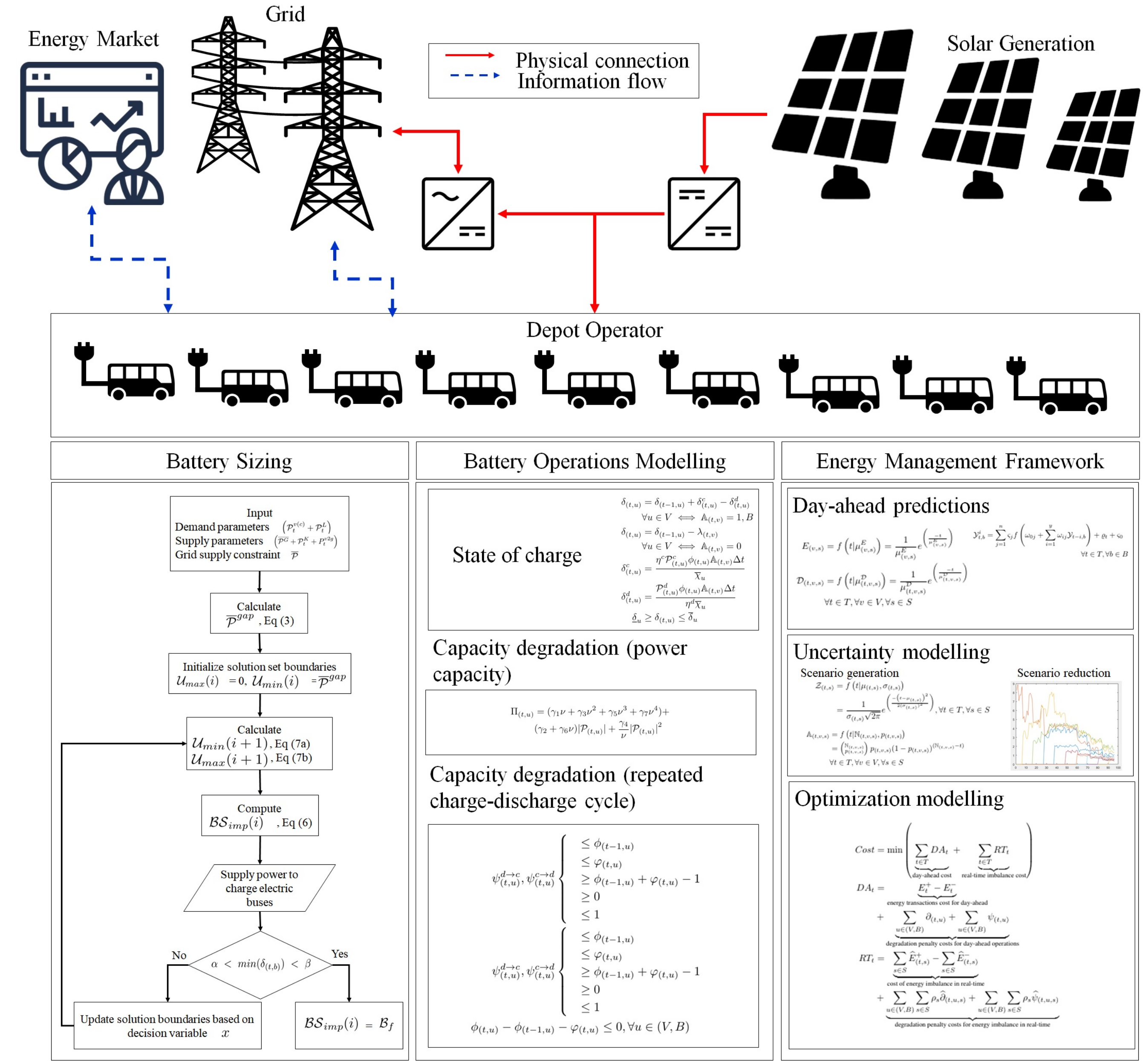


FIGURE 1: System architecture of the proposed energy management framework.

positive error terms is the total gap between the demand and supply. This is presented in eq. (3)

$$\overline{\mathcal{P}}^{gap} = \sum_{t=1}^{T} \begin{cases} \mathcal{P}_t^{gap} & \mathcal{P}_t^{gap} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

here $\overline{\mathcal{P}}^{gap}$ provides the maximum capacity bounds for the stationary battery to fill the gap between demand and supply in the constrained grid system. However, the system can still be operated at lower battery sizes while fulfilling all the energy needs. A feasible battery size $\mathcal{B}_f$ can be calculated using eq. (4)

$$\mathcal{B}_f = \begin{cases} \mathcal{P}_{max}^{gap} & \alpha < min(\delta_{(t,b)}) < \beta \\ \mathcal{BS}_{imp} & \text{otherwise} \end{cases} \tag{4}$$

here, $\alpha = lb * \mathcal{B}_f$ and $\beta = ub * \mathcal{B}_f$. $lb\&ub$ are the lower and upper bounds of state-of-charge respectively. The improved battery capacity $\mathcal{B}_{imp}$ is updated where $\mathcal{B}_f \neq \overline{\mathcal{P}}^{gap}$. A binary decision variable x is computed based on the battery state-of-charge. $x = 0$ for battery state-of-charge less than α, indicating undersized battery capacity estimation. While $x = 1$ for battery state-of-charge above β, indicating oversized battery capacity estimation. The states of x are presented in eq. (5). The subscripts $t\&b$ represents the time interval and stationary battery storage unit respectively.

$$x = \begin{cases} 0 & min(\delta_{(t,b)}) > \alpha \\ 1 & min(\delta_{(t,b)}) < \beta \end{cases} \tag{5}$$

The improved battery capacity i.e. $\mathcal{BS}_{imp}$ is calculated based on eqs. (6), (7a) and (7b).

$$\mathcal{BS}_{imp}(i) = \frac{(\mathcal{U}_{min}(i) + \mathcal{U}_{max}(i))}{2} \tag{6}$$

where i is the iteration number. $\mathcal{U}_{min}(i)$ and $\mathcal{U}_{max}(i)$ are the lower and upper bounds of the estimated battery capacity. The initial bounds are set at zero and $\overline{\mathcal{P}}^{gap}$ respectively, as presented in [21].

$$\mathcal{U}_{min}(i+1) = \begin{cases} \mathcal{U}_{min}(i) & x = 1 \\ \mathcal{BS}_{imp}(i) & x = 0 \end{cases} \tag{7a}$$

$$\mathcal{U}_{max}(i+1) = \begin{cases} \mathcal{BS}_{imp}(i) & x = 1 \\ \mathcal{U}_{max}(i) & x = 0 \end{cases} \tag{7b}$$

The upper and lower bounds are updated for each iteration based on the decision variable x. The algorithm repeats until the improved capacity $\mathcal{BS}_{imp}$ is calculated based on the defined constraints i.e. $\alpha < min(\delta_{(t,b)}) < \beta$. Once, a feasible battery size is calculated, it is then rounded-off to meet the commercially available battery capacities $\overline{\chi}_u^{com}$. This method estimates a feasible battery capacity which is available commercially, without using complicated non-linear optimization algorithms which takes longer duration for computing the optimal battery sizes.

VII. BATTERY OPERATIONS MODELLING

The proposed framework models the energy storage units $u \in (V, B)$, where V represents the set of electric bus batteries and B represents the set of stationary batteries. Operation of both the energy storage units are the same with the only exception of utilization of electric bus batteries for travel needs and their availability at the depot for charging-discharging operations. This paper mathematically models the state-of-charge, the cost of battery capacity degradation and the penalty cost to account for consecutive charge-discharge or discharge-charge cycles for longer battery life.

A. STATE OF CHARGE

The state-of-charge of energy storage units $u \in (V, B)$ for the day-ahead scheduling are generally modelled in eqs. (8a) to (8e). Here, $\delta_{(t,u)}$ represent the state-of-charge of energy unit $u \in V, B$ for time interval t. V represents the set of energy storage for electric buses and B is the set of stationary batteries. $\mathbb{A}_{(t,v)}$ is the binary availability matrix for electric buses at the depot, $\eta^c \& \eta^d$ are the charging & discharging efficiencies of the chargers. $\lambda_{(t,v)}$ in eq. (8b) is the state-of-charge consumed due to distance travel by electric buses when they are away from the depot. $\overline{\chi}_u$ represent the maximum capacity of the energy storage units. The upper and lower bounds for the state of charge of energy storage units are presented in eq. (8e).

$$\delta_{(t,u)} = \delta_{(t-1,u)} + \delta^c_{(t,u)} - \delta^d_{(t,u)} \quad \forall u \in V \iff \mathbb{A}_{(t,v)} = 1, B \tag{8a}$$

$$\delta_{(t,u)} = \delta_{(t-1,u)} - \lambda_{(t,v)} \quad \forall u \in V \iff \mathbb{A}_{(t,v)} = 0 \tag{8b}$$

$$\delta^c_{(t,u)} = \frac{\eta^c \mathcal{P}^c_{(t,u)} \phi_{(t,u)} \mathbb{A}_{(t,v)} \Delta t}{\overline{\chi}_u} \tag{8c}$$

$$\delta^d_{(t,u)} = \frac{\mathcal{P}^d_{(t,u)} \phi_{(t,u)} \mathbb{A}_{(t,v)} \Delta t}{\eta^d \overline{\chi}_u} \tag{8d}$$

$$\underline{\delta}_u \geq \delta_{(t,u)} \leq \overline{\delta}_u \tag{8e}$$

Similarly, the state-of-charge of energy storage units $u \in (V, B)$ for the energy imbalance in real-time are generally modelled in eqs. (9a) to (9e). Here $\widehat{\delta}_{(t,u,s)}$ represent the state-of-charge of energy unit $u \in V, B$. The subscripts $t \& s$ represents the time interval and respective scenario.

$$\widehat{\delta}_{(t,u,s)} = \widehat{\delta}_{(t-1,u,s)} + \widehat{\delta}^c_{(t,u,s)} - \widehat{\delta}^d_{(t,u,s)} \quad \forall u \in V \iff \widehat{\mathbb{A}}_{(t,v,s)} = 1, B \tag{9a}$$

$$\widehat{\delta}_{(t,u,s)} = \widehat{\delta}_{(t-1,u,s)} - \widehat{\lambda}_{(t,v,s)} \quad \forall u \in V \iff \widehat{\mathbb{A}}_{(t,v,s)} = 0 \tag{9b}$$

$$\widehat{\delta}^c_{(t,u,s)} = \frac{\eta^c \widehat{\mathcal{P}}^c_{(t,u,s)} \phi_{(t,u,s)} \widehat{\mathbb{A}}_{(t,v,s)} \Delta t}{\overline{\chi}_u} \tag{9c}$$

$$\widehat{\delta}^d_{(t,u,s)} = \frac{\widehat{\mathcal{P}}^d_{(t,u,s)} \widehat{\phi}_{(t,u,s)} \widehat{\mathbb{A}}_{(t,v,s)} \Delta t}{\eta^d \overline{\chi}_u} \tag{9d}$$

$$\underline{\delta}_u \geq \widehat{\delta}_{(t,u,s)} \leq \overline{\delta}_u \tag{9e}$$

B. CAPACITY DEGRADATION

The excessive charging and discharging cycles causes damage to the battery cells which results in battery capacity degradation. The cost of battery capacity degradation as a function of charging-discharging power is estimated based on the work done by authors in [19]. The cost of battery capacity degradation in the day-ahead energy market are calculated using eqs. (10) and (21c) .

$$\Pi_{(t,u)} = (\gamma_1 \nu + \gamma_3 \nu^2 + \gamma_5 \nu^3 + \gamma_7 \nu^4) + (\gamma_2 + \gamma_6 \nu)|\mathcal{P}_{(t,u)}| + \frac{\gamma_4}{\nu} |\mathcal{P}_{(t,u)}|^2 \tag{10}$$

here $\Pi_{(t,u)}$ represents the battery capacity degradation in kWh for energy storage units $u \in V, B$ for energy transactions in the day-ahead energy market. V is the set of electric buses and B is the set of stationary batteries. ν is the battery voltage and γ is the battery degradation coefficient.

Similarly, the cost of battery capacity degradation due to energy imbalance in real-time are calculated using eqs. (11) and (21g) .

$$\widehat{\Pi}_{(t,u,s)} = (\gamma_1 \nu + \gamma_3 \nu^2 + \gamma_5 \nu^3 + \gamma_7 \nu^4) + (\gamma_2 + \gamma_6 \nu)|\widehat{\mathcal{P}}_{(t,u,s)}| + \frac{\gamma_4}{\nu} |\widehat{\mathcal{P}}_{(t,u,s)}|^2 \tag{11}$$

here $\widehat{\Pi}_{(t,u,s)}$ represents the battery capacity degradation in kWh for energy storage units $u \in V, B$ due to energy imbalance in real-time.

C. CONSECUTIVE CYCLING

The battery storage is exploited when it is driven by market operations which can lead to frequent charge-discharge cycles in short spans of time. Repeated charging-discharging cycles can cause damage to battery cells and hence reduce the life of battery [20]. A penalty cost is imposed to minimize the unfeasible consecutive charge-discharge or discharge-charge cycles of battery storage. This is mathematically modelled in eqs. (12a) to (12c) for energy storage units in the day-ahead energy transactions market.

$$\psi^{d\to c}_{(t,u)}, \psi^{c\to d}_{(t,u)} \begin{cases} \le \phi_{(t-1,u)} \\ \le \varphi_{(t,u)} \\ \ge \phi_{(t-1,u)} + \varphi_{(t,u)} - 1 \\ \ge 0 \\ \le 1 \end{cases} \tag{12a}$$

$$\psi^{d\to c}_{(t,u)}, \psi^{c\to d}_{(t,u)} \begin{cases} \le \phi_{(t-1,u)} \\ \le \varphi_{(t,u)} \\ \ge \phi_{(t-1,u)} + \varphi_{(t,u)} - 1 \\ \ge 0 \\ \le 1 \end{cases} \tag{12b}$$

$$\phi_{(t,u)} - \phi_{(t-1,u)} - \varphi_{(t,u)} \le 0, \forall u \in (V, B) \tag{12c}$$

here, $\psi^{d\to c}_{(t,u)} \& \psi^{c\to d}_{(t,u)}$ are the respective binary variables to record the number of instances of consecutive discharge-charge and charge-discharge cycles for each energy storage unit $u \in (V, B)$. The aggregated penalty cost for such discharge-charge & charge-discharge cycles over the simulation cycle $t \in T$.

Similarly, the constraints for penalty cost to account for consecutive charge-discharge & discharge-charge cycles are mathematically modelled in eqs. (13a) to (13c) for energy storage units in the real-time energy imbalance transactions.

$$\widehat{\psi}^{d\to c}_{(t,u,s)}, \widehat{\psi}^{c\to d}_{(t,u,s)} \begin{cases} \le \widehat{\phi}_{(t-1,u,s)} \\ \le \widehat{\varphi}_{(t,u,s)} \\ \ge \widehat{\phi}_{(t-1,u,s)} + \widehat{\varphi}_{(t,u,s)} - 1 \\ \ge 0 \\ \le 1 \end{cases} \tag{13a}$$

$$\widehat{\psi}^{d\to c}_{(t,u,s)}, \widehat{\psi}^{c\to d}_{(t,u,s)} \begin{cases} \le \widehat{\phi}_{(t-1,u,s)} \\ \le \widehat{\varphi}_{(t,u,s)} \\ \ge \widehat{\phi}_{(t-1,u,s)} + \widehat{\varphi}_{(t,u,s)} - 1 \\ \ge 0 \\ \le 1 \end{cases} \tag{13b}$$

$$\widehat{\phi}_{(t,u,s)} - \widehat{\phi}_{(t-1,u,s)} - \widehat{\varphi}_{(t,u,s)} \le 0, \forall u \in (V, B) \tag{13c}$$

VIII. PROPOSED FRAMEWORK

Once the battery size is established based on the method discussed in section VI, a framework is required to optimize the charge-discharge scheduling of electric buses to minimize the cost of electricity for the depot operator. The proposed framework is composed of three main functionalities:

1) Day-ahead Prediction
2) Uncertainty Modeling
3) Optimal Scheduling

A. DAY-AHEAD PREDICTION

The proposed framework evaluates the optimal demand and supply energy bids based on the predicted run schedule, fixed site load, on-site solar generation and available stationary battery capacity. These bids are submitted in the day-ahead energy market. Any imbalances in energy from the predicted demand and supply energy bids are traded in real-time. The depot operator is the price taker and does not bid in the wholesale energy market to set the price of energy. It receives the day-ahead energy price signals one day prior to actual execution of energy transactions in the evening. The energy market coordinator determines the day-ahead energy tariffs and the market is cleared before the end of each day. The day-ahead energy tariff signal for buying and selling energy are $\pi^+_t \& \pi^-_t$ respectively. These signals are received from the energy market coordinator and therefore these signals are not forecasted. The detailed description of the energy market is presented in [22]. The depot operator predicts the fixed load, on-site generation and the electric bus run schedules to estimate the energy demand and supply bids in the day-ahead wholesale energy market.

1) Fixed loads & on-site generation forecast

The fixed loads, on-site generation and electric bus run schedules are forecasted based on the artificial neural network (ANN) model using the historical time series data. ANN is a reliable forecasting method in forecasting load profiles [23]. This paper utilizes a back-propagation learning algorithm which is a commonly used algorithm in the feed-forward ANN. The forecast values are estimated based on eq. (14).

$$\mathcal{Y}^i_{t,b} = \sum_{j=1}^{n} \varsigma_j f\left(\omega_{0j} + \sum_{i=1}^{y} \omega_{ij} \mathcal{Y}_{t-i,b}\right) + \varrho_t + \varsigma_0 \quad \forall t \in T, \forall b \in B \tag{14}$$

where $\mathcal{Y} \in \{\widehat{\mathcal{P}}^K_t \& \widehat{\mathcal{P}}^L_t\}$. $\widehat{\mathcal{P}}^K_t$ and $\widehat{\mathcal{P}}^L_t$ are the respective forecasts for the on-site distributed energy resource generation and fixed site loads. n is the number of hidden layers in the ANN model, the weights from the layers are indicated by $\omega_{ij}$and δ_j . The ϱ_t is a random shock, where $\omega_{0j}$and ς_0 represent the bias terms of the ANN.

2) Run schedule forecast

The electric bus run schedule is generally prepared by the depot operator for each bus to cover different routes in the vicinity. The run schedule for each electric bus have the information of departure time, arrival time, dwell time and the distance travel for each day of the week. Optimal route scheduling is beyond the scope of this paper and it is assumed that the run schedules are prepared by the depot operator using an independent optimal route scheduler. It is assumed that the run schedules are prepared such that each electric bus is charged at the depot only. The run schedule parameters are used to calculate the availability matrix, status matrix and the distance travel needs. These parameters are used for estimating charging needs of electric buses and energy available for vehicle-to-grid and vehicle-to-building services.

B. UNCERTAINTY MODELING

The forecasts are never accurate due to various reasons which include stochastic nature of human behavior, unpredictable weather conditions and unexpected traffic conditions. The inaccuracies in forecasts leads to uncertainty in cost estimations. The deterministic optimization models estimate the cost of electricity based on single set of inputs, while ignoring large number of possible scenarios. This paper deals with the uncertainty factor by considering large number of possible scenarios generated using the Monte-Carlo simulation technique. However, simulating large number of scenarios requires high computation time. Therefore a scenario reduction technique is used to reduce the number of scenarios for appropriate computation time without loosing significant statistical attributes of the generated scenarios.

1) Scenario generation

Large number of possible scenarios are generated using Monte-Carlo simulation. The probability distributions functions (PDFs) for respective forecasted parameters are estimated based on the historical time series data.

2) Fixed site load, on-site solar generation & energy tariffs

The PDFs for the fixed site load, on-site solar generation and energy tariffs for real-time energy imbalance transactions are estimated based on eq. (15). $\mathcal{Z}_{(t,s)}$ represents the generic estimation of the PDF for fixed site load, on-site solar generation and energy tariffs such that $\mathcal{Z}_{(t,i)} \in \{\mathcal{P}^{L}_{(t,s)}, \mathcal{P}^{K}_{(t,s)}, \widehat{\pi}^{+}_{(t,s)} \& \widehat{\pi}^{-}_{(t,s)}\}$

$$\mathcal{Z}_{(t,s)} = f\left(t|\mu_{(t,s)}, \sigma_{(t,s)}\right) = \frac{1}{\sigma_{(t,s)}\sqrt{2\pi}} e^{\left(\frac{-\left(t-\mu_{(t,s)}\right)^2}{2(\sigma_{(t,s)})^2}\right)}, \forall t \in T, \forall s \in S \quad (15)$$

where μ^s_t and σ^s_t represent the mean and standard deviation of the historical data, respectively at time interval t for scenario s.

3) Run schedule

Generally, the schedules are fixed. However, practically the departure time, arrival time, distance traveled by the buses and the energy efficiency of the buses vary from the proposed run schedules because of various uncontrolled reasons specifically route elevations, temperature, and traffic conditions on the road. The run schedule is the most important parameter in determining the charge-discharge schedule for electric buses.

1) Availability and Status Matrix

The availability matrix i.e. $\mathbb{A}_{(t,v,s)}$ is the binary parameter that indicates the availability of the bus at the depot for charging-discharging. $\mathbb{A}_{t,v,s} = 0$ when the respective bus v is away from the depot at time t for scenario s. Conversely, $\mathbb{A}_{t,v,s} = 1$ when the electric bus is at the depot for charging-discharging. The generic estimation of the availability matrix can be modelled using eq. (16).

$$\begin{aligned}\mathbb{A}_{(t,v,s)} &= f\left(t|\mathbb{N}_{(t,v,s)}, p_{(t,v,s)}\right) \\ &= \binom{\mathbb{N}_{(t,v,s)}}{p_{(t,v,s)}} p_{(t,v,s)} (1 - p_{(t,v,s)})^{(\mathbb{N}_{(t,v,s)}-t)} \\ &\forall t \in T, \forall v \in V, \forall s \in S \qquad (16)\end{aligned}$$

where $\mathbb{N}_{(t,v,s)}$ represents the number of scenarios for each EV to estimate the availability of an EV at home for charging/discharging and $p_{(t,v,s)}$ is the success probability of respective scenario s.

A status matrix i.e. $\mathcal{X}_{(t,v,s)}$ is extracted from the availability matrix to clearly distinguish between the different states of the electric buses. Four key states of the buses are available, not available, departed and arrived. The status matrix helps in scheduling the charge-discharge cycles of respective electric buses to manage the state-of-charge for upcoming trips as per the run schedule. The electric bus status is determined according to Algorithm 1, which identifies when a particular electric bus arrives at the depot or departs from the depot.

2) Distance and Energy Efficiency

The actual range of electric vehicles can vary significantly compared to the manufacturer's claims [24]. Therefore, scenarios are generated for the energy effi-

Algorithm 1 Status Matrix

for $t \in T$ **do**
  for $v \in V$ **do**
    for $s \in S$ **do**
      if $\mathbb{A}_{(t,v,s)} = 1$ **then**
        if $\mathbb{A}_{(t,v,s)} = 0$ **then**
          $\mathcal{X}_{(t,v,s)} = 3$ ▷ Arrived
        else
          $\mathcal{X}_{(t,v,s)} = 1$ ▷ Available
      else
        if $\mathbb{A}_{(t-1,v,s)} = 1$ **then**
          $\mathcal{X}_{(t,v,s)} = 4$ ▷ Departed
        else
          $\mathcal{X}_{(t,v,s)} = 2$ ▷ Not-Available
end procedure

ciency of electric buses instead of using a constant number. Similarly, the distance travelled by buses can vary from the run schedule due to unpredictable traffic conditions. The PDFs for estimating the energy efficiency i.e. $E_{(v,s)}$ and the distance travelled i.e. $\mathcal{D}_{(t,v,s)}$ by the electric buses are estimated using eqs. (17) and (18) respectively, based on the historical time series dataset.

$$E_{(v,s)} = f\left(t|\mu^{E}_{(v,s)}\right) = \frac{1}{\mu^{E}_{(v,s)}} e^{\left(\frac{-t}{\mu^{E}_{(v,s)}}\right)} \tag{17}$$

$$\mathcal{D}_{(t,v,s)} = f\left(t|\mu^{\mathcal{D}}_{(t,v,s)}\right) = \frac{1}{\mu^{\mathcal{D}}_{(t,v,s)}} e^{\left(\frac{-t}{\mu^{\mathcal{D}}_{(t,v,s)}}\right)} \tag{18}$$

$$\forall t \in T, \forall v \in V, \forall s \in S$$

where $\mu^{E}_{(v,s)} \& \mu^{\mathcal{D}}_{(t,v,s)}$ represents the mean energy efficiency and mean distance traveled by electric bus v at time t for scenario s respectively.

4) Scenario reduction

The computation time required to simulate large number of scenarios is extremely high, which is not feasible for day-ahead optimal scheduling of electric bus charging-discharging. Therefore, the proposed paper applies a scenario reduction technique to reduce the number of scenarios for feasible computation time without loosing any significant statistical attributes of the potential scenarios. The reduction algorithms used in the paper, determines a subset of the initial scenario set and assigns new probabilities to the refined scenarios. The algorithm is based on repeated reduction phenomenon. The scenario tree building algorithms successively reduce the number of nodes of individual scenarios by modifying the tree structure and by aggregating similar scenarios. The detailed explanation of the algorithms applied in this paper are presented in [25].

C. OPTIMIZATION MODELING

The optimzation model is designed to minimize the cost of electricity for the depot operator. The details of optimization modelling are presented in the following subsections.

1) Objective Function

The objective function aims to minimize the cost of electricity for the depot operator. It is the sum of the cost of electricity bought & sold in the day-ahead energy market and the energy imbalance trading in real-time. It is presented in eq. (19).

$$Cost = \min \left(\underbrace{\sum_{t\in T} DA_t}_{\text{day-ahead cost}} + \underbrace{\sum_{t\in T} RT_t}_{\text{real-time imbalance cost}} \right) \tag{19}$$

where $Cost$ is the aggregated cost of electricity for the depot operator, DA_t is the cost of electricity in the day-ahead energy market and RT_t is the expected cost of uncertainties based on energy imbalance transactions in real-time.

$$DA_t = \underbrace{E^{+}_t - E^{-}_t}_{\text{energy transactions cost for day-ahead}} + \underbrace{\sum_{u\in(V,B)} \partial_{(t,u)} + \sum_{u\in(V,B)} \psi_{(t,u)}}_{\text{degradation penalty costs for day-ahead operations}} \tag{20a}$$

$$RT_t = \underbrace{\sum_{s\in S} \widehat{E}^{+}_{(t,s)} - \sum_{s\in S} \widehat{E}^{-}_{(t,s)}}_{\text{cost of energy imbalance in real-time}} + \underbrace{\sum_{u\in(V,B)} \sum_{s\in S} \rho_s \widehat{\partial}_{(t,u,s)} + \sum_{u\in(V,B)} \sum_{s\in S} \rho_s \widehat{\psi}_{(t,u,s)}}_{\text{degradation penalty costs for energy imbalance in real-time}} \tag{20b}$$

$E^{+}_t \& E^{-}_t$ are the respective costs of energy bought and sold in the day-ahead energy market, while $\widehat{E}^{+}_t \& \widehat{E}^{-}_t$ are the imbalance energy bought and sold in real-time. $\partial_{(t,u)} \& \widehat{\partial}_{(t,u,s)}$ are the cost of battery capacity degradation for energy storage units $u \in (V, B)$ in the day-ahead energy market and energy imbalance trade in real-time respectively. Where, B is the set of stationary battery and V is the set of electric buses. Each term in eqs. (19), (20a) and (20b) is mathematically modelled in eqs. (21a) to (21h).

$$E^{+}_t = \mathcal{P}^{+}_t \pi^{+}_t \Delta t \tag{21a}$$

$$E^{-}_t = \mathcal{P}^{-}_t \pi^{-}_t \Delta t \tag{21b}$$

$$\partial_{(t,u)} = \Pi_{(t,u)} \theta_u \tag{21c}$$

$$\psi_{(t,u)} = \psi^{c\to d}_{(t,u)} + \psi^{d\to c}_{(t,u)} \tag{21d}$$

$$\widehat{E}^{+}_{(t,s)} = \widehat{\mathcal{P}}^{+}_{(t,s)} \widehat{\pi}^{+}_{(t,s)} \Delta t \tag{21e}$$

$$\widehat{E}^{-}_{(t,s)} = \widehat{\mathcal{P}}^{-}_{(t,s)} \widehat{\pi}^{-}_{(t,s)} \Delta t \tag{21f}$$

$$\widehat{\partial}_{(t,u,s)} = \widehat{\Pi}_{(t,u,s)} \theta_u \tag{21g}$$

$$\widehat{\psi}_{(t,u,s)} = \widehat{\psi}^{c\to d}_{(t,u,s)} + \widehat{\psi}^{d\to c}_{(t,u,s)} \tag{21h}$$

$\pi^{+}_t \& \pi^{-}_t$ are the respective tariffs for buying and selling energy in day-ahead energy market. $\widehat{\pi}^{+}_t \& \widehat{\pi}^{-}_t$ are the buying and selling tariffs for energy imbalance trade in real-time. θ_u is the cost of battery capacity degradation in \$/Wh for the energy storage units $u \in V, B$. $\psi_{(t,u)}, \& \widehat{\psi}_{(t,u,s)}$ are the penalty costs to account for consecutive charge-discharge or discharge-charge cycles for the energy storage units $u \in V, B$ in the day-ahead energy market and energy imbalance trade in real-time respectively. B is the set of stationary battery and V is the set of electric buses.

2) Constraints

The objective function is formulated subject to following constraints.

1) Auxiliary Constraints: υ_t & φ_t are the auxiliary binary variables for day-ahead energy market transactions and represent the power drawn from the grid and power

supplied back to the grid respectively. eqs. (22a) to (22c) are the constraints to linearize the power transactions form grid. For $\upsilon_t = 1$ and $\varphi_t = 0$, the depot operator draws power from the grid. Otherwise, for $\upsilon_t = 0$ and $\varphi_t = 1$, the depot operator feeds back power to the grid.

$$\mathcal{P}_t^+ \leq \upsilon_t \overline{\mathcal{P}} \tag{22a}$$

$$\mathcal{P}_t^- \leq \varphi_t \overline{\mathcal{P}} \tag{22b}$$

$$\upsilon_t + \varphi_t \leq 1 \tag{22c}$$

Similarly, $\widehat{\upsilon}_t$ & $\widehat{\varphi}_t$ are the auxiliary binary variables for imbalance energy transactions in real-time and represent the power drawn from the grid and power supplied back to the grid respectively. eqs. (23a) to (23c) are the constraints to linearize the power transactions form grid. For $\widehat{\upsilon}_t = 1$ and $\widehat{\varphi}_t = 0$, the depot operator draws power from the grid. Otherwise, for $\widehat{\upsilon}_t = 0$ and $\widehat{\varphi}_t = 1$, the depot operator feeds back power to the grid.

$$\sum_{s\in S} \widehat{\mathcal{P}^+}_{(t,s)} \leq \widehat{\upsilon}_t \overline{\mathcal{P}} \tag{23a}$$

$$\sum_{s\in S} \widehat{\mathcal{P}^-}_{(t,s)} \leq \widehat{\varphi}_t \overline{\mathcal{P}} \tag{23b}$$

$$\widehat{\upsilon}_t + \widehat{\varphi}_t \leq 1 \tag{23c}$$

2) Power Flow Constraints:
The power balance equation of day-ahead energy transactions for the depot is presented in eq. (24).

$$\mathcal{P}_t^+ - \mathcal{P}_t^- = \mathcal{P}_t^L + \sum_{u\in(V,B)} \mathcal{P}_{(t,u)}^c - \sum_{u\in(V,B)} \mathcal{P}_{(t,u)}^d - \mathcal{P}_t^K \tag{24}$$

where $\mathcal{P}_t^+$ is the power drawn from the grid, $\mathcal{P}_t^-$ is the power fed back to the grid, $\mathcal{P}_t^L$ is the fixed site load, $\mathcal{P}_t^K$ is the on-site solar generation, $\mathcal{P}_{(t,u)}^c \& \mathcal{P}_{(t,u)}^d$ are the respective charging & discharging powers of the energy storage units $u \in V, B$. Similarly, the power balance equation of imbalance energy transactions in real-time is presented in eq. (25).

$$\begin{aligned}\widehat{\mathcal{P}}_t^+ - \widehat{\mathcal{P}}_t^- = &\sum_{s\in S} \rho_{(t,s)}^L \widehat{\mathcal{P}}_{(t,s)}^L + \sum_{u\in V,B} \sum_{s\in S} \mathcal{P}_{(t,u,s)}^c \\ &- \sum_{u\in V,B} \sum_{s\in S} \mathcal{P}_{(t,u,s)}^d - \sum_{s\in S} \rho_{(t,s)}^K \widehat{\mathcal{P}}_{(t,s)}^K\end{aligned} \tag{25}$$

where $\widehat{\mathcal{P}}_{(t,s)}^+$ is the power drawn from the grid, $\widehat{\mathcal{P}}_{(t,s)}^-$ is the power fed back to the grid, $\widehat{\mathcal{P}}_{(t,s)}^L$ is the fixed site load, $\widehat{\mathcal{P}}_{(t,s)}^K$ is the on-site solar generation, $\mathcal{P}_{(t,u,s)}^c \& \mathcal{P}_{(t,u,s)}^d$ are the respective charging & discharging powers for energy storage $u \in V, B$. $\rho_{(t,s)}^L \& \rho_{(t,s)}^K$ are the probability of success for each scenario s of fixed site load and on-site solar generation at time t such that $\sum_{s\in S} \rho_{(t,s)}^L = 1 \& \sum_{s\in S} \rho_{(t,s)}^K = 1$.

3) Maximum Power Demand Constraints:
A constraint for maximum aggregated power drawn by the depot operator from the grid i.e. $\overline{\mathcal{P}}$, is set to manage the peak demand from grid's perspective while minimizing the cost of energy consumption for the depot operator. The maximum aggregated power capacity constraints are modelled using eqs. (26a) and (26b). Another constraint applied to the proposed framework i.e. $\overline{\mathcal{P}}(V)$, limits the maximum aggregated power due to charging/discharging of electric buses at any given time. This constraint is worked out such that the network capacity limits provided by the grid operator are never exceeded and is modelled in eqs. (26c) to (26f) for respective day-ahead and real-time energy imbalance transactions. This constraint does not restrict any electric bus from charging or discharging, instead it regulates the charging/discharging power to manage the load profile.

$$\mathcal{P}_t^+ + \sum_{s\in S} \widehat{\mathcal{P}}_{(t,s)}^+ \leq \overline{\mathcal{P}} \tag{26a}$$

$$\mathcal{P}_t^- + \sum_{s\in S} \widehat{\mathcal{P}}_{(t,s)}^- \leq \overline{\mathcal{P}} \tag{26b}$$

$$\sum_{v\in V} \mathcal{P}_{(t,v)}^c \leq \overline{\mathcal{P}}(V) \tag{26c}$$

$$\sum_{v\in V} \mathcal{P}_{(t,v)}^d \leq \overline{\mathcal{P}}(V) \tag{26d}$$

$$\sum_{v\in V} \sum_{s\in S} \widehat{\mathcal{P}}_{(t,v,s)}^c \leq \overline{\mathcal{P}}(V) \tag{26e}$$

$$\sum_{v\in V} \sum_{s\in S} \widehat{\mathcal{P}}_{(t,v,s)}^d \leq \overline{\mathcal{P}}(V) \tag{26f}$$

IX. NUMERICAL VALIDATION

The adequacy of the proposed energy management framework is validated through numerical simulations. The details of datasets used for numerical validation are presented in the following sub-sections.

A. SIMULATION SETUP

The proposed energy management framework is developed using general algebraic modelling system (GAMS) and MATLAB. The electric bus run schedules are modelled in MATLAB. The objective function eqs. (19), (20a) and (20b) and the associated constraints eqs. (22a) to (22c), (23a) to (23c), (24), (25) and (26a) to (26f) are formulated in the GAMS and solved using the Cplex solver [26] with zero absolute and relative optimality gaps. The simulation was setup on an Intel Core i7 2.00 GHz computer with 16 GB RAM. Data exchange (GDX) is used for communications between MATLAB and GAMS. The MATLAB neural network toolbox (nntool) has been used to train the feed-forward ANNs. MATLAB provides builtin transfer functions that have been used for the hidden and output layers as follows: hyperbolic tangent sigmoid (tansig) for the hidden neurons; a pure linear function (purelin) for the output neurons [23].

1) Electric bus parameters

The proposed energy management framework is assessed by means of simulation on a hypothetical bus depot. The bus depot operates 50 electric buses with bidirectional energy flow capabilities to participate in the grid support services and earn revenue for the depot operator. The depot is supplied with constrained power supply capped at 1MW. A study of 4,135 buses showed that the daily vehicle consumption may vary by as much as 450 kWh,ranging from 100 kWh to 550 kWh for a complete day of operation and from 1.1 kWh/km to 2.2 kWh/km depending on the journey conditions [27]. For simplicity, we have considered that all the electric buses have a rated battery capacity of 300 kWh with a usable battery capacity of 270 kWh (i.e. 90% depth of discharge). The parameters for the run schedule i.e. arrival time, departure time and distance travel during the run, are assumed hypothetically based on the bus runs during a routine week. The efficiencies for each bus are estimated as per the models defined in section VIII-B2.

2) Charging infrastructure parameters

It is assumed that there is a bidirectional charger for every two electric buses. Each bus has access to a dedicated plug, such that the maximum charging-discharging power for each charger does not exceed 50kW. This means, when a charger is fully occupied i.e. two electric buses are connected, the maximum power for each bus is rated at 25kW. Therefore, the aggregated charging capacity for the entire depot in case all the buses are connected and charging, is 1.25MW. The charging and discharging efficiencies of the charger are considered to be 95%.

3) Fixed site load and on-site DER generation

The fixed site load is assumed equivalent to a normal office building load. The bus depot is equipped with the solar PV panels as the on-site distributed energy resource (DER) generation. The size of the solar panels installation is estimated based on the size of the roof of the buses. Based on the solar panels available commercially as used in [28], [29], it has been worked out that the bus depot which can accommodate 50 buses, has sufficient space to install 350kW (peak) capacity solar panels. The load profiles for the forecasted fixed site load, generation profiles for the forecasted solar PV and their scenarios are presented in fig. 2.

4) Energy tariff

This paper assumes that the depot operator is a price-taker from the day-ahead energy market and the energy imbalance transactions in real-time. The forecasts and scenarios of tariffs for energy transactions in day-ahead and energy imbalance transactions in real-time are computed based on the historical wholesale energy market tariffs of NEM (National Electricity Market) [30]. The forecast and scenarios for buying and selling energy in the day-ahead energy market are presented in figs. 3a and 3b. Similarly, the forecasts and scenarios for the energy transactions in real-time are presented in figs. 3c and 3d.

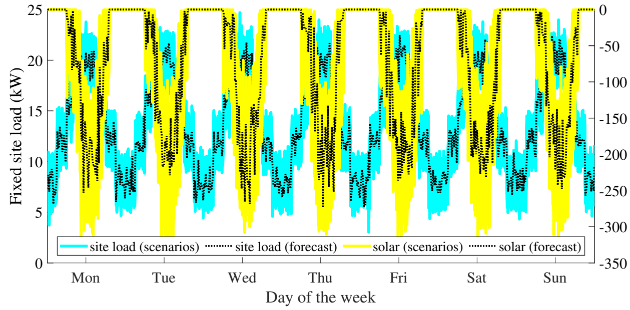


FIGURE 2: Fixed loads and on-site generation for a typical week

B. CASE STUDIES

To evaluate the effectiveness of the proposed energy management framework, case studies have been conducted for two scheduling strategies and the cost of electricity for the depot operator is analyzed. All strategies are evaluated using the same set of input data and parameters described in section IX.

1) Uncoordinated scheduling - Strategy 1

As the name implies, the uncoordinated strategy only evaluates the charging schedule of electric buses at the depot without utilizing the vehicle-to-grid flexibilities of the energy storage units installed in electric buses. The strategy works on greedy algorithm, which charges each electric bus as soon at it arrives at the depot without considering the price signals of time-of-use tariff. The strategy utilizes all the energy from the on-site solar generation to charge the electric buses and the stationary battery and sells any remaining energy to the grid. This strategy is deterministic and is referred as the base case to compare the effectiveness of the proposed strategy. The mathematical model of this strategy is mathematically modelled in eqs. (27a) to (27d).

$$Cost_{s1} = \min \Bigg(\underbrace{E_t^+ - E_t^-}_{\text{energy transactions cost for day-ahead}} + \underbrace{\sum_{u\in(V,B)} \partial_{(t,u)} + \sum_{u\in(V,B)} \psi_{(t,u)}}_{\text{degradation penalty costs for day-ahead operations}} \Bigg) \tag{27a}$$

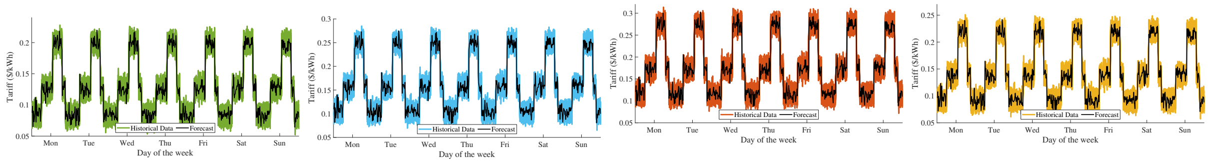
subject to

$$\mathcal{P}_t^+ - \mathcal{P}_t^- = \mathcal{P}_t^L + \sum_{u\in(V,B)} \mathcal{P}_{(t,u)}^c - \mathcal{P}_t^K \tag{27b}$$

$$\delta_{(t,u)} = \delta_{(t-1,u)} + \delta_{(t,u)}^c \tag{27c}$$

$$eqs.\ (8b), (8c), (8e) and\ (10)$$

$$eqs.\ (21a) to\ (21d) and\ (22a) to\ (22c) \tag{27d}$$



(a) Day-ahead energy market tariffs for selling energy. (b) Day-ahead energy market tariffs for buying energy. (c) Real-time imbalance energy market tariffs for buying energy. (d) Real-time imbalance energy market tariffs for selling energy.

FIGURE 3: Energy tariffs for a typical week

2) Deterministic scheduling - Strategy 2

This strategy uses deterministic approach for optimal charge-discharge scheduling of energy storage units while also accounting for capacity degradation of the energy storage units due to charging-discharging power capacity and repeated charge-discharge cycles. The optimization model of this strategy is mathematically modelled in eq. (28a).

$$Cost_{s2} = \min \Bigg(\underbrace{E_t^{+} - E_t^{-}}_{\text{energy transactions cost for day-ahead}} + \underbrace{\sum_{u \in (V,B)} \partial_{(t,u)} + \sum_{u \in (V,B)} \psi_{(t,u)}}_{\text{degradation penalty costs for day-ahead operations}} \Bigg) \tag{28a}$$

subject to

$$\begin{aligned} &eqs.\ (8a) to\ (8e) \\ &eqs.\ (21a) to\ (21d) \\ &eqs.\ (22a) to\ (22c) and\ (24) \\ &eqs.\ (10) and\ (12a) to\ (12c) \end{aligned} \tag{28b}$$

X. RESULTS

This section presents the results of the battery sizing method presented in section VI and compares the results of all the strategies presented in section IX-B with the proposed framework. Comparisons are mainly made in terms of aggregated electricity cost and the penalty cost for energy storage units capacity degradation. The aggregated results of the scheduling strategies are presented in table 1 for a typical week.

A. BATTERY SIZE

Based on the modified method described in section VI for estimating the capacity of stationary energy storage unit and the input parameters defined in section IX, the calculated battery size is 1372 kWh with maximum charging-discharging power capacity of 270 kW. It took 3s to estimate battery size including the estimation of one year charging needs of electric buses at the depot. All the scheduling strategies described in section IX-B used the same capacity of the stationary energy storage. All the strategies described in section IX-B are processed as linear programming optimization problems as the capacity of battery storage

B. EFFECT OF SCHEDULING STRATEGIES ON ELECTRICITY COST

The objective functions of the proposed energy framework presented in section VIII-C, the optimization model of strategy-1 presented in section IX-B1 and strategy-2 in section IX-B2 are formulated to minimize the cost of electricity for the depot operator. The results of aggregated cost of electricity for all the strategies are presented in table 1 and compared in the following sub-sections.

1) Strategy-1 vs proposed framework

The uncoordinated scheduling strategy as described in section IX-B1, does not account for vehicle-to-grid flexibilities. The electric buses are charged as soon as the electric buses arrive at the depot. The on-site solar generation is utilized to charge the electric buses and the stationary battery. Any access energy from the solar generation is sold to the grid. It can be noted from the results presented in table 1 that the aggregated cost of electricity for this strategy is the highest compared to any other strategy as expected. The total cost of electricity for the proposed framework is 34% less than strategy-1, as the proposed framework utilizes the flexibilities of batteries on the wheels through vehicle-to-grid operations.

2) Strategy-2 vs proposed framework

The deterministic scheduling strategy as described in section IX-B2, does not account for the uncertainty associated with the predicted parameters. The optimization model minimize the cost of electricity based on the predicted input parameters. Based on the results presented in table 1, it can be noted that the aggregated cost of electricity for the proposed framework is significantly lower than strategy-2. The total cost of electricity for the proposed framework is 23% less than strategy-2. This is because the stochastic approach of the proposed framework considers the uncertainties and

TABLE 1: Aggregated results of scheduling strategies

	Scheduling Strategies		
	Strategy-1	Strategy-2	Proposed method
DA demand bids (kWh)	314,228	409,919	368,546
DA supply bids (kWh)	54,961	151,375	109,592
RT demand bids (kWh)	-	-	74,511
RT supply bids (kWh)	-	-	76,003
Net energy cost ($)	$6,359	$5,470	$4,188
Capacity degradation cost ($)	$21.8	$20.5	$50.5

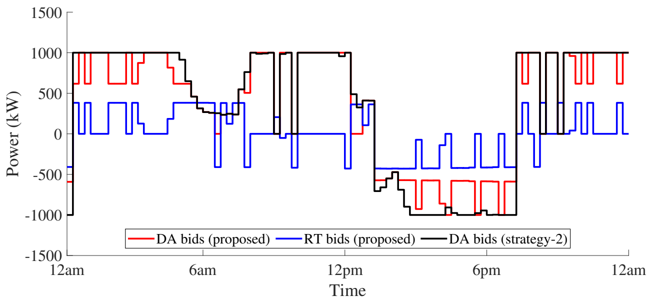


FIGURE 4: Demand and supply bids for proposed framework (stochastic) and strategy-2 (deterministic)

the expected cost of energy imbalance in real-time while determining the schedule in the day-ahead stages. Therefore, the proposed framework submits conservative demand and supply quantity bids in day-ahead energy market when the uncertainty is higher, compared to the deterministic approach of strategy-2. This can be seen in fig. 4.

C. EFFECT OF SCHEDULING STRATEGIES ON PENALTY COSTS

The proposed energy management framework also accounts for the capacity degradation of the energy storage units due to charging-discharging power and also repeated charge-discharge cycles in terms of penalty costs. The results of the aggregated penalty costs on account of energy storage units capacity degradation for all the strategies are presented in table 1 and compared in the following sub-sections.

1) Strategy-1 vs proposed framework

The cost of energy storage units capacity degradation for the proposed framework (50.5$) is more than double the strategy-1 (21.8$). However, the cost savings offered by the proposed framework i.e. 2,170$ compared to strategy-1, which is much higher than the penalty cost difference due to capacity degradation i.e. 28.7$.

2) Strategy-2 vs proposed framework

It can be noted from table 1 that the penalty cost of energy storage capacity degradation for the proposed framework (50.5$) is higher than strategy-2. However, the cost savings offered by the proposed framework i.e. 1,281$ compared to strategy-2, is much higher than the penalty cost difference due to capacity degradation i.e. 29.9$.

XI. DISCUSSION

This paper proposes a comprehensive energy management framework to minimize the cost of electricity for the electric bus depot with constrained grid power supply. In the first stage it estimates the capacity of a stationary energy storage unit for the bus depot to mitigate the demand and supply gap due to constrained grid power supply. The proposed framework utilizes the batteries installed in the electric buses through vehicle-to-grid flexibilities while also accounting for the energy storage units capacity degradation cost. The stochastic approach of the proposed method enables reduced risk estimations for the depot operator. The effectiveness of the proposed energy framework is validated by simulation studies for a hypothetical bus depot operator in Australia.

A comparison with the state-of-the-art scheduling strategies show that the proposed energy framework can provide cost savings upto 34% compared to an uncoordinated scheduling strategy. The proposed energy framework formulates the day-ahead scheduling as stochastic optimization problem to minimize cost. The proposed framework estimates conservative energy bids for day-ahead while factoring the expected cost of real-time imbalance based on large number of potential scenarios. The case studies indicate that the proposed stochastic method is capable of accounting for the real-time energy imbalance trading for uncertain scenarios of fixed site load demand, on-site solar generation, and real-time market prices. Therefore, the proposed energy framework submits conservative demand and supply energy bids in day-ahead compared to the deterministic scheduling i.e. strategy-2, when the uncertainty is high and exploits the price elasticity in both markets to minimize the cost of electricity. And it can be seen from table 1 that the proposed energy framework can provide cost savings up to 23% compared to strategy-2. Most scheduling strategies presented in existing literature [9]–[18] does not account for uncertainty modelling.

The proposed framework also models the operations of energy storage units precisely. It accounts for battery capacity degradation due to charging-discharging power capacity and also capacity degradation due to repeated charging-discharging cycles unlike the models presented in [8]–[18]. Results presented in table 1 show that the penalty cost due to energy storage unit capacity degradation is high for the proposed framework. However, the savings in cost of electricity for the proposed framework are significantly higher compared to the penalty cost for energy storage capacity degradation.

One of the limitations of the proposed energy framework is that the proposed method for battery sizing does not provide the optimal size of the stationary battery. Addition of battery optimization model in the proposed energy management framework would transform the existing linear optimization problem to a non-linear optimization problem, which takes long computation time to solve the problem. Therefore, a separate model is used to estimate the capacity of stationary battery to maintain the linear nature of the optimization problem for the proposed energy management framework. The proposed battery sizing method provides a reasonable estimate for battery capacity selection. However, future work will focus on designing a method to estimate optimal size of the stationary battery with minimal computation time. Future work will also focus on improving the effectiveness of the uncertainty model to minimize the risk of under or over estimation for the depot operator. Nonetheless, simulations and case studies indicate promising results of the proposed method in terms of actual financial cost savings for the depot operator.

XII. CONCLUSION

A comprehensive energy management framework is proposed in this paper to minimize the cost of electricity for the electric bus depot with constrained power supply from the grid. In the first stage, the proposed energy framework estimates the size of the stationary battery for the depot to mitigate the shortfall of power supply from the grid. The proposed framework estimates demand and supply energy bids for day-ahead energy market while factoring the expected cost of energy imbalance in real-time market based on large number of potential scenarios. It submits conservative energy bids in day-ahead when the uncertainty is high and exploits the price elasticity in both markets i.e. day-ahead and real-time, to minimize the cost of electricity for the depot operator. The proposed energy framework also accounts for capacity degradation of the energy storage units due to charging-discharging power capacity as well as repeated charge-discharge cycles.

The proposed methodology is validated by comparing it with the state-of-the-art scheduling strategies for a typical week. Simulation results indicate the efficacy of the proposed energy management framework and show that the proposed energy management framework provides 34% more cost savings compared to uncoordinated scheduling strategy. Results also show up to 23% more net energy cost savings compared to the counterpart deterministic strategy. However, excess charging-discharging of electric buses to buy and sell energy at optimal tariffs also leads to battery capacity degradation. The model does not completely prevent the frequent charge-discharge cycles as this will result in the reduction of cost savings for the depot operator, rather the charge-discharge cycles are optimally minimized so that maximum cost savings can be attained subject to minimal battery capacity degradation in terms of penalty costs.

The proposed framework does not provide the optimal size of the stationary battery as the battery optimization models are non-linear in nature and they take long computation time to solve the problem. Therefore, a separate model is used to estimate the capacity of stationary battery. However, future work will focus on designing a method to estimate optimal size of the stationary battery with minimal computation time. Future work will also focus on estimating the degree of uncertainty based on statistical parameters to interpret the risk for the depot operator. Nonetheless, simulations and case studies indicate promising results of the proposed method in terms of actual financial cost savings for the depot operator.

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XIII. APPENDIX

Nomenclature

Indices and Sets

$t \in T$	Time intervals
$u \in (V, B)$	set of energy storage units (V = elecric buses, B = stationary battery)
$s \in S$	Scenarios

Parameters

$E_{(v,s)}$	Energy efficiency of electric bus for scenario s [$/kWh]
$\mathcal{D}_{(t,v,s)}$	Distance travelled by electric bus for scenario s [km]
$\widehat{\mathcal{P}}^L_{(t,s)}$	On-site DER generation for scenario s [kW]
$\widehat{\mathcal{P}}^K_{(t,s)}$	Fixed site load for scenario s [kW]
$\widehat{\lambda}_{(t,v,s)}$	State-of-charge consumed due to distance travel by electric buses for scenario s [%]
$\lambda_{(t,v)}$	State-of-charge consumed due to distance travel by electric buses [%]
$\mathbb{A}_{(t,v)}$	Availability matrix of electric buses [0,1]
$\mathcal{Y}^i_{t,b}$	Forecast for fixed site load and on-site solar generation [kW]
$\mathcal{Z}_{(t,s)}$	Scenario generation for fixed site load, on-site solar generation and real-time tariff
$\mathcal{X}_{(t,v)}$	Status matrix of electric buses
$\mathcal{P}^K_t$	On-site DER generation [kW]
$\mathcal{P}^L_t$	Fixed site load [kW]
π^+_t	Energy buying tariff for day-ahead energy market [$/kWh]
π^+_t	Energy selling tariff for day-ahead energy market [$/kWh]
$\widehat{\pi}^+_t$	Energy buying tariff for energy imbalance trade in real-time [$/kWh]
$\widehat{\pi}^+_t$	Energy selling tariff for energy imbalance trade in real-time [$/kWh]
$\underline{\delta}_u$	Minimum state-of-charge of energy storage unit [%]
$\overline{\delta}_u$	Maximum state-of-charge of energy storage unit [%]
θ_u	Cost of energy storage capacity degradation [$/kWh]
$\overline{\mathcal{P}}(V)$	Maximum aggregated charging-discharging power limit for electric buses [kW]]
η^c	Charging efficiency of the charger [%]
η^d	Discharging efficiency of the charger [%]
$\overline{\chi}^{com}_u$	Capacity of commercially available energy storage unit [kWh]
α	Upper bound for energy storage unit state-of-charge [%]
β	Lower bound for energy storage unit state-of-charge [%]
$\overline{\mathcal{P}}$	Grid constraint - maximum power supply from grid [kW]
$\overline{\chi}_u$	Maximum capacity of the energy storage unit [kWh]
$\mathcal{F}_{v2g}$	Vehicle-to-grid flexibility factor [%]
ρ_s	Probability of scenario s

Variables

$Cost$	Aggregated cost of electricity based on proposed energy framework [$]
$Cost_{s1}$	Aggregated cost of electricity based on strategy-1 [$]
$Cost_{s2}$	Aggregated cost of electricity based on strategy-2 [$]
DA_t	Cost of day-ahead energy transactions [$]
RT_t	Cost of real-time imbalance energy transactions [$]
E^+_t	Cost of energy bought from grid by depot operator in day-ahead energy market [$]
E^-_t	Cost of energy sold to grid by depot operator in day-ahead energy market [$]
$\widehat{E}^+_{t,s}$	Cost of energy bought from grid by depot operator in real-time for scenario s [$]
$\widehat{E}^-_{t,s}$	Cost of energy sold to grid by depot operator in real-time for scenario s [$]
$\widehat{\delta}_{(t,u,s)}$	State-of-charge of energy storage unit for scenario s [%]
$\delta_{(t,u)}$	State of charge of energy storage unit [%]
$\widehat{\mathcal{P}}^c_{(t,u,s)}$	Charging power of energy storage unit for scenario s [kW]
$\widehat{\mathcal{P}}^d_{(t,u,s)}$	Discharging power of energy storage unit for scenario s [kW]
$\mathcal{P}^c_{(t,u)}$	Charging power of energy storage unit [kW]
$\mathcal{P}^d_{(t,u)}$	Discharging power of energy storage unit [kW]
$\Pi_{(t,u)}$	Energy storage unit capacity degradation [kWh]
$\widehat{\Pi}_{(t,u,s)}$	Energy storage unit capacity degradation for scenario s [kWh]
$\psi^{d \to c}_{(t,u)}$	Binary variable to record consecutive discharge-charge cycles [0,1]
$\psi^{c \to d}_{(t,u)}$	Binary variable to record consecutive charge-discharge cycles [0,1]

$\widehat{\psi}^{d \to c}_{(t,u,s)}$	Binary variable to record consecutive discharge-charge cycles for scenario s [0,1]
$\widehat{\psi}^{c \to d}_{(t,u,s)}$	Binary variable to record consecutive charge-discharge cycles for scenario s [0,1]
$\partial_{(t,u)}$	Penalty cost for capacity degradation cost due to charging-discharging power capacity [$]
$\psi_{(t,u)}$	Penalty cost for capacity degradation cost due to repeated charging-discharging cycles [$]
$\widehat{\partial}_{(t,u,s)}$	Penalty cost for capacity degradation cost due to charging-discharging power capacity for scenario s [$]
$\widehat{\psi}_{(t,u,s)}$	Penalty cost for capacity degradation cost due to repeated charging-discharging cycles for scenario s [$]
$\mathcal{P}^{c}_{t}$	Aggregated charging demand of electric buses without battery storage [kW]
P^{v2g}_{t}	Estimated vehicle-to-grid flexibilities for battery sizing [kWh]
$\mathcal{P}^{gap}_{t}$	Demand and supply gap for battery sizing [kW]
$\mathcal{B}_f$	Feasible battery size [kWh]
$\overline{\mathcal{P}^{gap}}$	Maximum demand and supply gap [kWh]