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A comparative techno-economic assessment of bidirectional heavy duty and light duty plug-in electric vehicles operation: A case study

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ABSTRACT

The proliferation of electric vehicles (EVs) all around the world offers both challenges and opportunities to build a sustainable city and transportation system. Bidirectional charging capabilities at workplace charging facilities (e.g., as part of a microgrid) have made the overall economic optimization more attractive on one hand, but also more complex on the other hand. This paper investigates the cost optimization problem for bidirectional charging at a workplace microgrid connected to two different buildings to determine the optimal framework for a combination of both heavy-duty and light-duty electric vehicles (HDEV and LDEV). A deep learning-based model has been developed to forecast the 15-minute solar generation and building power consumption. Real-time travel profile data has been used to represent the temporal uncertainty of electric vehicle charging. The cost optimization problem is formulated as a Mixed Integer Programming (MIP) model which also addresses battery life degradation. Furthermore, a comprehensive economic analysis has been carried out to analyze the payback period, peak reduction, and cost savings for two different buildings at the same workplace with both on-board and off-board charger configurations. It has been found that HDEV is a better cost-effective solution in comparison to LDEV in terms of energy cost reduction and payback periods. Net metering capability leads to higher energy savings and peak reductions in most cases.

1. Introduction

1.1. Motivation

Sustainable transportation and carbon emission-free energy usage policies around the world have encouraged people to adopt more Plug-in Electric Vehicles (PEVs) for both personal and business purposes. PEV is becoming an integral part of smart cities due to its contribution towards sustainable energy goals in many countries. The infrastructure and technological development in the EV industry has made the influx of both heavy-duty and light-duty electric vehicles (HDEV and LDEV) possible in the U.S. States like California have a goal of deploying 5 million zero-emission vehicles by 2025 and 250 thousand EV stations by 2030 (Transportation Electrification, 2022). The California Public Utilities Commission (CPUC) and other agencies have now dedicated nearly $1B in HDEV and LDEV charging infrastructure. The plan is to have over 240 thousand level II EV Charging Stations (EVCS) (a power rating of 6-7.2 kW is representative of level II EVCS) and over 10 thousand level III/DC Fast Charging (DCFC) EVCS (a power rating of 30-50 kW or more is representative of level III EVCS) by 2025 (Transportation Electrification, 2022, California Targets Nearly $400M to Fill Gaps in EV Charging Infrastructure, 2022). The combined implementation of HDEV and LDEV infrastructure will make transportation electrification easier to be widely implemented.

While many pilot projects on transportation electrification usually focus on either HDEV or LDEV deployment, there are not many pilot implementations that consider both as part of the same infrastructure. There can be three types of EVCS available for the users' charging purposes which are residential, workplace, and public, respectively. Both medium-duty and heavy-duty electric vehicles (MDEV and HDEV) have similar potential to reduce carbon emission and encourage emission-free shared transportation. But their EVCS deployment differs from the LDEVs in terms of their high-power requirements and less

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Nomenclature

t	Time slot index
T	Total time period
n_{ld}	light duty PEV index
n_{hd}	heavy duty PEV index
l_1	charging decision binary variable index for EV
l_2	discharging decision binary variable index for EV
N_{ld}	Set of light duty PEVs
N_{hd}	Set of heavy duty PEVs
L_{ch}	Set of charging binary variables
L_{disch}	Set of discharging binary variables
Δt	Time interval
b_1	Charging decision binary variable for BESS
d_1	Discharging decision binary variable for BESS
SOC_{EV}	State of Charge of EV
$SOC_{min,EV}$	Minimum SOC for EV
$SOC_{max,EV}$	Maximum SOC for EV
$\eta_{ch,EV}$	EV charging efficiency
$\eta_{disch,EV}$	EV discharging efficiency
$P_{ins,EV}$	Instantaneous power consumption by any EV
r_m	Resistance of EV motor
D_{tire}	Diameter of the EV tires
k_a	Armature constant
φ	Magnetic flux
m_{EV}	Total mass of the EV
a	Acceleration of EV while driving
k_{aero}	Aerodynamic drag coefficient
v	Velocity of EV on a trip
f_{rl}	Rolling friction coefficient
g	Acceleration due to gravity
$P_{EV,ch}$	Power transferred from grid to each vehicle (kW)
$P_{EV,disch}$	Power transferredfrom each vehicle to grid (kW)
$P_{EV,ch\ max}$	Maximum charging power for EV (kW)
$P_{EV,disch\ max}$	Maximum discharging power for EV (kW)
P_{grid}	Power from grid to building
P_{solar}	Power generated from solar
$P_{building}$	Power consumption of the building
$P_{EV,disch,total}$	Total Power transferred from vehicle to grid (kW)
$P_{EV,ch,total}$	Total Power collected from grid to vehicle (kW)
$A_{EV,n_{ld}}$	Availability matrix for light duty EV
$A_{EV,n_{hd}}$	Availability matrix for heavy duty EV
C_e	Price of energy purchased from grid ($/kWh)
$C_{battery}$	Cost of Li-ion battery ($/kWh)
Cap_{init}	Initial Capacity of the EV battery
Cap_{useful}	Useful Capacity of the EV battery
$Deg_{calendar}$	Calendar degradation of the EV battery
Deg_{cycle}	Cycle degradation of the EV battery
DOD	Depth of Discharge
a1,b,c	Fitting parameters for cycle degradation

maneuverability. Using a high energy consuming building/infrastructure equipped with renewable energy and large parking spaces as a charging/discharging hub may solve these problems. This hub can be used by passenger vehicles and any HDEV using nearby routes. This will also reduce the overall infrastructure cost and necessary upgrades in the distribution system. Moreover, the coordinated operation of both will offer opportunities to reduce the overall operation and energy cost of the infrastructure. Their vehicle-to-grid operation can also help to lessen the adverse impacts on the grid and reduce problematic peaks. The current trend of renewable energy sources available in these distribution-level microgrids can also play an important role by charging the EVs to maximize renewable consumption. The DCFC infrastructure will also help to accommodate the HDEVs requirements while at the same time satisfying LDEV needs without requiring any separate infrastructure. While the deployment of the EVCS can make EV charging/discharging more convenient, their cost-benefit analyses need to be performed for the optimal operation of EVCS.

EVs in general will soon become a significant percentage of the daily electrical peak demand and optimizing their charging/discharging schedule will be required to help manage peak demand. The heat waves of August 2020 in California caused peak electrical demand in the early evening with low solar production. To prevent the grid from collapsing completely, these situations lead to rotating blackouts due to the results of heat waves. The influx of EVs in the near future will challenge the current grid infrastructure even further since EVs are likely to be plugged in after the daily commute during the evening hours. The potential higher peaks generated from EVs need to be investigated and optimized before large-scale EVCS is deployed.

1.2. Related Research Activity

HDEV and LDEV optimal scheduling have been explored in many other studies. Electric buses are often considered an early example of HDEV implementation around the world. Electric bus charging station scheduling is optimized considering an energy storage system followed by sensitivity analysis (Pan, Wu, Feng, & Ji, 2020, Zhang, 2019). The daily operating cost is minimized but the battery loss model used there to minimize the cost is inconclusive. In (Basma et al., 2020, Beekman & Van Den Hoed, 2016), electric bus charging optimization is done under varying operating conditions. Depot charging, end-line charging, and opportunity charging stations are explored to minimize energy and battery replacement costs. The cost-benefit analysis is executed in (Jiang et al., 2018) to show that a trade-off between the fixed cost and charging cost is needed for the optimal fleet size. In-depot charging has an impact on overall cost minimization and in (Gormez, Haque, & Sozer, 2021) cost optimization is carried out for an opportunity charging bus network. A cost optimal design strategy is also proposed for heavy-duty electric vehicle drivetrains (Kampker et al., 2019). While the goal of these studies is optimizing the energy costs for HDEVs, the opportunities of incorporating LDEVs using the same infrastructure, their coordinated operation, and reducing the payback periods are not discussed.

Evolutionary algorithms are widely explored by Mixed Integer Programming (MIP) formulation to execute the cost-benefit analysis for mostly LDEVs. In (Chen et al., 2016), a mixed-integer linear programming (MILP) problem is formulated to compare the effectiveness between the coordinated and uncoordinated charging strategies, while ignoring the battery degradation cost. In (Moradipari et al., 2020), a MILP is formulated to minimize the daily operation cost for electric bus fleets and the strategy is validated by Stanford University's shuttle data. In (Houbbadi et al., 2018), evolutionary algorithms are used to reduce electricity costs and battery aging for electric buses. The optimal charging strategy shows improvements in both cost reduction and improving battery life. In (Zahedmanesh, Muttaqi, & Sutanto, 2021), a three-stage cooperative energy management system is proposed for a virtual energy hub that provides the minimum operational cost. The virtual energy hub only comprises an electric bus and a simplistic representation of the real test case scenarios. Moreover, the uncertainties are not addressed properly and are more focused on overall energy management. A bi-objective optimization model is proposed in (Zhou, Liu, Wei, & Golub, 2021) for battery-electric bus deployment and the trade-off between environmental fairness and resource investment.

In (Heredia et al., 2020), an economic evaluation is carried out for

Table 1
Summary of related works.

Reference	Research Focus	Summary
(Pan, Wu, Feng, & Ji, 2020, Zhang, 2019)	HDEV CS scheduling	Minimizing the energy and battery replacement costs
(Basma et al., 2020, Beekman & Van Den Hoed , 2016)	HDEV CS scheduling	Minimizing the operational cost
(Jiang et al., 2018, Gormez, Haque, & Sozer, 2021, Kampker et al., 2019)	HDEV cost-benefit analysis	Cost optimization for HDEV operation
(Zahedmanesh, Muttaqi, & Sutanto, 2021, Zhou, Liu, Wei, & Golub, 2021)	HDEV energy management and deployment	Operational cost minimization and trade-off between environmental benefit and investments
(Chen et al., 2016, Moradipari et al., 2020, Houbbadi et al., 2018, Sufyan et al., 2020)	LDEV charging	MILP-based and Heuristic cost optimization
(Heredia et al., 2020, Luo et al., 2013, Luo et al., 2013)	LDEV Case Studies	Cost optimization for LDEV operation
(Brinkel et al., 2020)	Bidirectional LDEV charging	Trade-off between cost and emission optimization
(Koubaa et al., 2020, Oda et al., 2018, Yang, Zhang, & Dong, 2020)	Case studies for Bidirectional EVs	Economic advantages of V2G, quick EV charging and different EV infrastructures
(Yan, Zhang, & Kezunovic, 2019)	EV customer satisfaction	Optimizing bidirectional EVCS
(David & Al-Anbagi, 2017, Tamura, 2020, Singh & Tiwari, 2020, Bagheri Tookanlou, Marzband, Al Sumaiti, & Mazza, 2020, Fan & Chen, 2019, Rodríguez-Molina, Castillejo, Beltran, & Martínez-Núñez, 2020)	Cost benefit analyses	Frequency regulation by EV, EV grid integration, PEV owners' benefits
(Hu, Bu, & Terzija, 2021, Fanti, Mangini, Roccotelli, & Silvestri, 2022, Corinaldesi, Lettner, & Auer, 2022, Cheng et al., 2020)	Electric car sharing	Voltage regulation and cost optimization
(Qureshi, Alhudhaif, & Jeon, 2021, Firouzjah, 2022)	EVCS Parking Lot energy management	Energy security and profit maximization

adaptive charging algorithm implementation in 16 level-II EVCS and 1 DCFC at the U.S. National Renewable Energy Laboratory. The study mainly focuses on the operation and installation cost along with the reduction in demand charge. The study lacks the modeling of EV and battery degradation. The opportunity for different EVCS, EV, and the payback period of the implementation were not investigated. In (Luo et al., 2013, Luo et al., 2013), a two-stage MILP optimization model is proposed for a coordinated vehicle to grid (V2G) and a case study in China was used to validate it. The peak load reduction is done in the first stage and the load fluctuation is taken care of in the second stage. In (Brinkel et al., 2020), a multi-objective optimization method is applied to find the trade-off between the cost and emission of bidirectional EV charging. Next, the reinforcement cost of the grid is determined. In (Sufyan et al., 2020), the Firefly algorithm is used to find the optimal system cost for EV charging coordination.

Case studies have also been carried out to show the economic benefits of V2G (Koubaa et al., 2020) and reducing the waiting time for EV quick charging (Oda et al., 2018), and for different EV charging infrastructure subsidy policies (Yang, Zhang, & Dong, 2020). A four-stage optimization method has been proposed to maximize customer satisfaction for EV charging on a bidirectional EVCS equipped with renewable energy resources (Yan, Zhang, & Kezunovic, 2019). Cost-benefit analyses were done in smart grid environments for frequency regulation by EV (David & Al-Anbagi, 2017, Tamura, 2020), EV grid integration (Singh & Tiwari, 2020, Bagheri Tookanlou, Marzband, Al Sumaiti, & Mazza, 2020, Fan & Chen, 2019), and privately owned PEV owners (Rodríguez-Molina, Castillejo, Beltran, & Martínez-Núñez, 2020). Studies are also done to show electric car-sharing opportunities for reducing congestion and making the transportation system more sustainable. Innovative strategies are proposed in (Hu, Bu, & Terzija, 2021, Fanti, Mangini, Roccotelli, & Silvestri, 2022) for voltage regulation and electric car relocation in a car-sharing environment. Electric car sharing can also help to reduce the overall electricity cost and incidental peaks as well (Corinaldesi, Lettner, & Auer, 2022, Cheng et al., 2020). EV energy management and charging scheduling systems are proposed to provide a secured EV management strategy (Qureshi, Alhudhaif, & Jeon, 2021) and energy cost reduction in public parking lots (Firouzjah, 2022) in sustainable cities and societies. These studies aim to achieve two primary objectives: developing an energy management approach that can resist unauthorized access and maximizing profits for the parking lots, respectively. The idea of having an adaptive charging infrastructure that can host both HDEV and LDEVs is not presented in these studies. The summary of all the relevant works are mentioned in Table 1.

1.3. Contribution and Paper Organization

While there are many studies done that evaluate the pros and cons of residential and public PEV charging strategies, workplace charging strategies along with the coordinated HDEV and LDEV operation have not been widely analyzed. Moreover, as people spend a significant amount of time at their workplace, workplace charging strategies are very important from both the user and building owner's perspective. Even though PEVs can perform bidirectional charging and vehicle-to-building operation, vehicle-to-grid services are not implemented widely yet. The real-time implementation of V2G is a big challenge due to the unavailability of the infrastructure and V2G capable vehicles. Hence, these strategies are yet under development and are mostly executed in pilot projects. All the studies discussed above have been mostly focused on LDEV or HDEV optimization separately. The combined benefits possible from operating both at the same workstation have not yet been explored, let alone their implementations. A comprehensive cost-benefit analysis considering the infrastructure and implementation cost is still absent in the literature which will be very important for the mass deployment of HDEV and LDEV in the near future.

Further, all the literature discussed above lacks a comprehensive cost-benefit analysis to determine the optimal framework for LDEV and HDEV implementation in a distribution-level microgrid. One can raise several questions regarding the LDEV and HDEV integration at the same workstation: 1) How cost-efficient is HDEV implementation in comparison to LDEV implementation and what is the optimal cost including both HDEV and LDEV integration? 2) How do V2G and the battery degradation impact the overall cost-benefit of the microgrid owner? 3) What happens to the optimal cost solution for different PEV owners' behaviors and metering scenarios? 4) What is the payback period of different cost-optimal strategies? This paper tries to find answers to all these questions and attempts to bridge the gap in the current literature. The novel contributions of this paper can be summarized as follows:

1 A comprehensive cost-benefit analysis to find out the optimal framework for a combined LDEV and HDEV implementation.
2 A novel data-driven methodology to optimize the overall energy cost that integrates deep learning based prediction model and the PEV availability matrices.
3 Analyzing net metering and charger based benefits to the microgrid owner.
4 Modeling the uncertainties associated with load, solar, and PEV along with the battery degradation and introducing the key factors

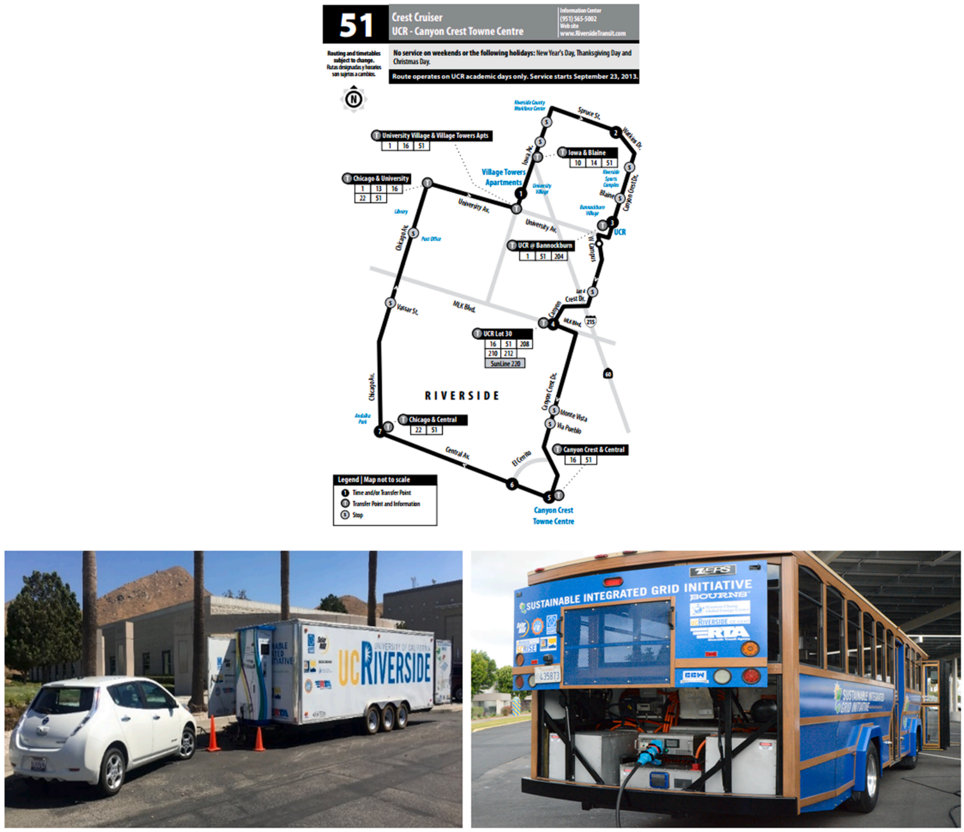

Fig. 1. Top: HDEV Route and Bottom: LDEV with the battery energy storage trailer (left) and HDEV with the on-board charger (right).

for LDEV and HDEV deployment on workplace-integrated microgrids.

5 Assessing the impacts of fleet size on the optimal framework problem.

This paper is organized as follows: Section 2 describes the methodology, Section 3 discusses the problem formulation and constraints, Section 4 includes the results and discussions, and Section 5 concludes the paper and discusses future work.

2. Methodology

As an example of implementing this analytical approach presented in this methodology, we consider the microgrid at the College of Engineering – Center for Environmental Research & Technology (CE-CERT) at the University of California Riverside. This microgrid incorporates multiple level II and one level III EV charger. One of the CE-CERT buildings (Building 1084) is used for administrative activities and another (Building 1200) is used for research activities. The CE-CERT microgrid consists of a 180 kW solar PV system at each building (Ula, Yusuf, & Hasan, 2019). The electrical load of the 1084 building follows a regular office load pattern whereas the electrical load of the 1200 building is relatively larger with a more uncertain pattern which depends on the types and schedules of research activities. The regular work hours are from 8 am to 5 pm on weekdays. The current infrastructure allows the electric bus to be plugged into any of the buildings through an inverter located inside a 500 kWh stationary battery energy storage trailer. There are five EVCS connected to the 1084 building electrical distribution panel. The daily solar production in the 1084 building is more than the average load consumption whereas the average load consumption is higher in the 1200 building. 1084 building is a Tier 1 (maximum demand $<$ 100 kW) building and the 1200 building is Tier 4 (maximum demand is 250-500 kW) building (Electric Rules, & Rates, 2022).

The LDEV with the V2G charger and the battery energy trailer, HDEV, and it's designated route are shown in Fig. 1.

2.1. Predicting Building and Solar Data

The building load pattern depends on the occupancy along with the solar generation being intermittent due to weather. The energy cost is calculated by the electric utilities based on the 15-minute rolling average energy consumption. For a better estimation of energy cost, a 15-minute ahead building load and solar prediction are done for each of the buildings. Statistical approaches such as ARIMA don't provide a good estimation for short-term time series prediction (Yusuf, Faruque, Hasan, & Ula, 2019). It fails to capture the intermittent changes caused by the load and solar production and is more suitable to use for daily/yearly prediction with a definite trend. On the other hand, Long Short-Term Memory (LSTM) network can capture these irregularities upon data availability. Hence, LSTM is applied for the 15-minute ahead time series prediction. This network is applied on the Keras platform using Tensorflow at the backend (Chollet at el, 2015). A rolling-horizon approach is implemented for prediction. The input data are updated for each time slot. 30 days of data are used for training the model initially. Then the 1st timestamp data of the next day is predicted. The Adam optimizer is used (Kingma & Ba, 2017), and the batch size (1), number of layers (8), and number of epochs (5000) have been tuned to find the best fit for the fitted model. The prediction results do not change much with a higher number of layers and epochs. A typical summer month data is used for the prediction. Fig. 2 is showing the predicted data for the 31st of July for both of the buildings and Table 2 is showing the error metrics for the prediction which shows that solar generation is predicted with a very low root mean square error (RMSE). The prediction is good enough to follow the building load pattern but the RMSE increases with a high load deviation for the 1200 building.

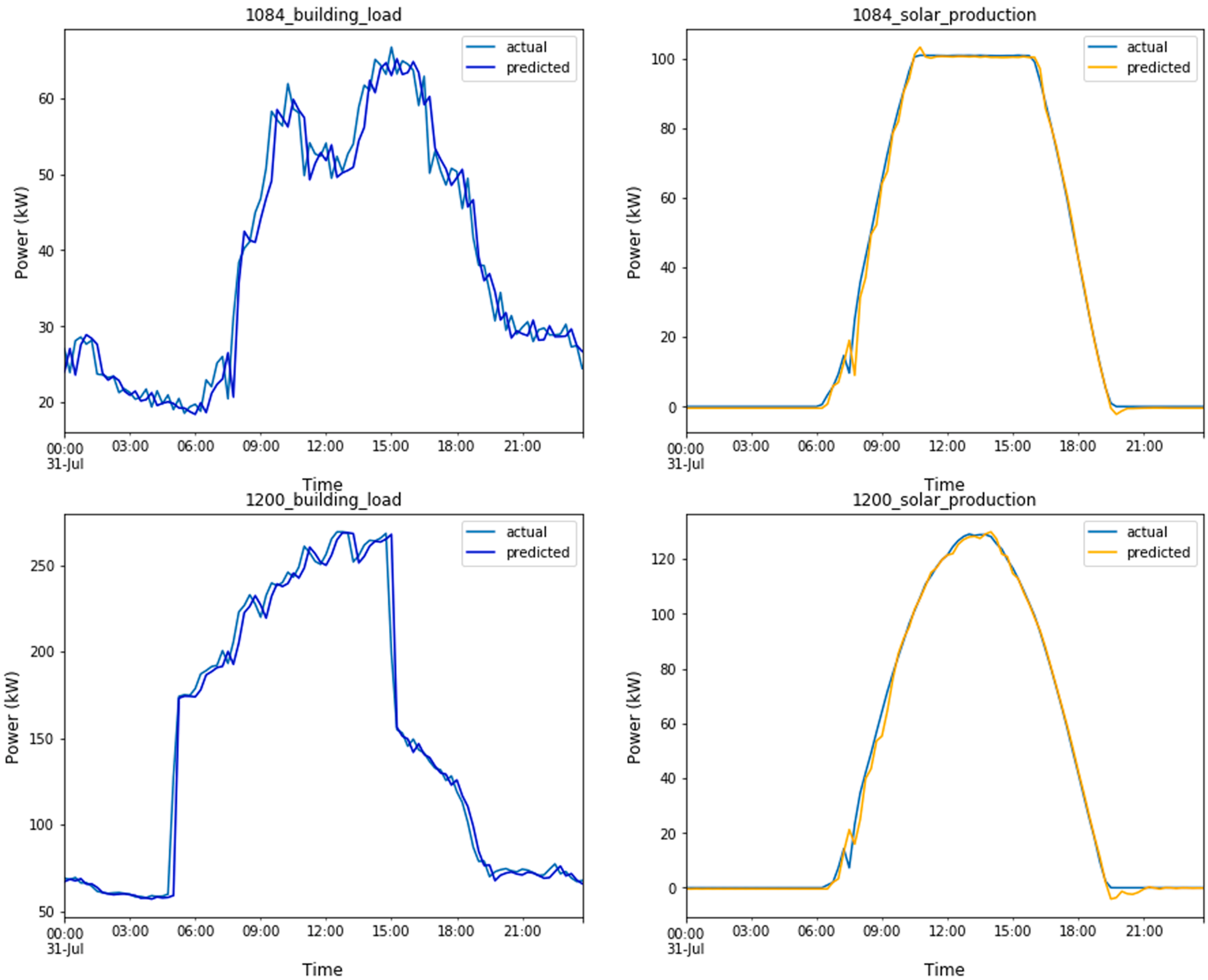

Fig. 2. Predicting building load and solar generation for both of the buildings.

Table 2
Error metrics for prediction.

Prediction (kW)	RMSE	Prediction (kW)	RMSE
1084 building load	3.14	1084_solar	2.39
1200_building_load	11.12	1200_solar	2.57

2.2. Heavy Duty PEV Data

When considering HDEV activity, we utilize data from an electric trolley bus that operates on a fixed route around UC Riverside. The battery pack used in the electric trolley is composed of 540 cylindrical lithium iron phosphate cells arranged in a 5P108S (5 parallel, 108 series) pattern that provides 345.6 V and a capacity of 155.52 kWh nominal. The cells are laid out across 12 ventilated enclosures, with each enclosure featuring its battery management system (BMS) modules. The on-board charger takes in AC voltage from the utility grid and converts it to the necessary DC voltage to charge the battery pack. The charger is currently configured to charge at one of three selectable levels corresponding to 33, 67, and 100 A DC and allows a maximum of 40 kW power level. The bus has been tested along a specific route (Route 51) as part of the Riverside Transit Agency schedule (Riverside Transit Agency 2022). The total route is 14.97 km long with an additional stop at CE-CERT. To measure the average kWh needed per kilometer, the bus is tested for multiple days with both loaded and unloaded conditions. The average energy consumption is 0.92 kWh/km and 0.72 kWh/km for loaded and unloaded conditions, respectively. Using the same route every day is similar to the schedule of school buses. It is assumed that the bus will complete two round trips each day as school buses do, one in the morning and one in the afternoon. The energy consumption per trip can be estimated by using the following equations that can be applied to any kind of route. The instantaneous power consumed by an EV is extracted from (Wu, Freese, Cabrera, & Kitch, 2015) and modified as follows.

$$P_{ins,EV} = \frac{r_m \times D_{tire}^2}{4 \times k_a^2 \times \varphi^2}\left(m_{EV}a + k_{aero}v^2 + f_{rl}m_{EV}g + m_{EV}g\sin\theta\right)^2 + v\left(k_{aero}v^2 + f_{rl}m_{EV}g + m_{EV}g\sin\theta\right) + m_{EV}av \quad (1)$$

The first two terms in (1) are the power losses from motor and travel resistance, respectively. The last term is the power generated from acceleration/deceleration. The integral of this instantaneous power consumption throughout the whole trip will result in (2).

$$E_{total\ per\ trip} = \int_{t=1}^{T} P_{ins,EV}(t)dt \quad (2)$$

2.3. Light Duty PEV Data

For our LDEV analysis, we consider two light-duty electric vehicles

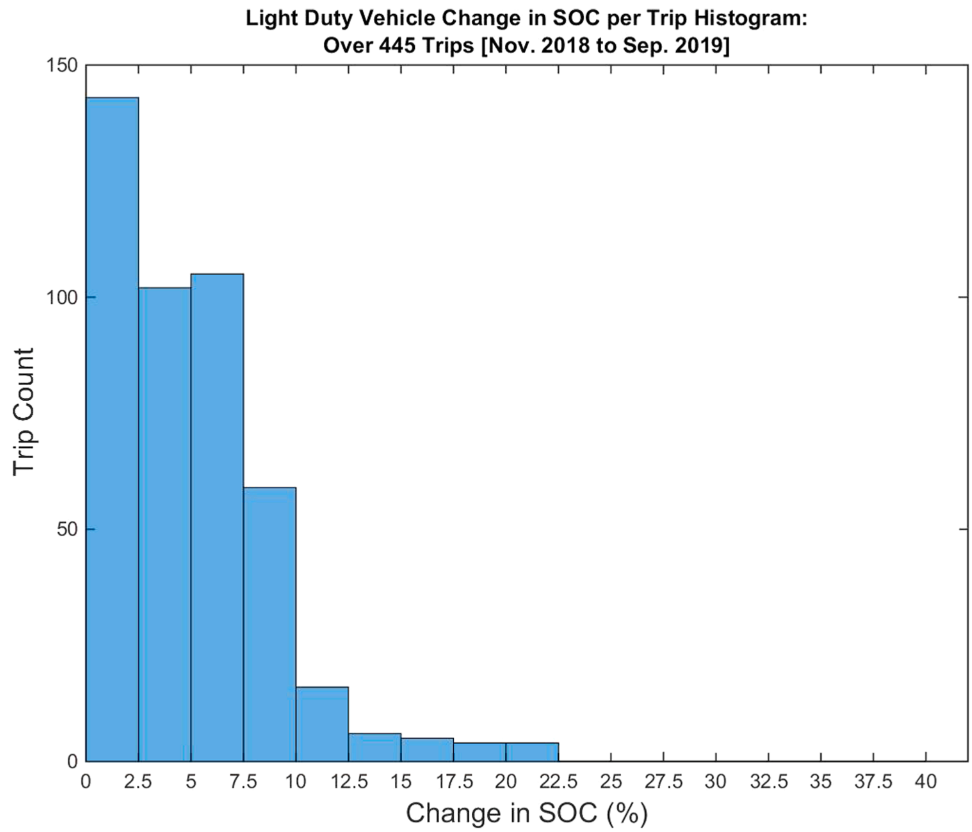

Fig. 3. Change in SOC per trip for both PEVs.

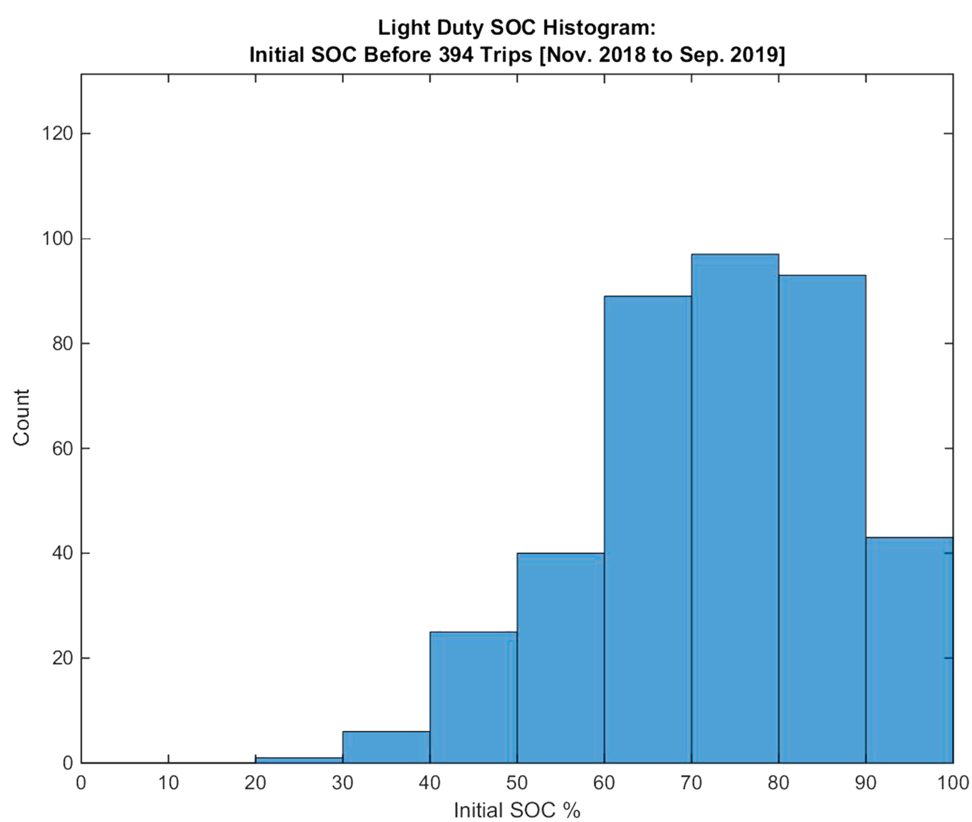

Fig. 4. Initial SOC per trip for both PEVs.

that are available for the employees of these buildings for short to medium-distance travels for attending meetings. Both light-duty PEVs are 2013 Nissan Leaf electric vehicles that have the capability of V2G operation. Both have 24 kWh battery capacity with a capability of fast charging/discharging given that fast-charging bidirectional EV stations are available. The recent models of Nissan Leaf have a 40 kWh or 62 kWh battery capacity (Nissan Leaf 2022). As 40 kWh battery capacity PEV is the most common one used by consumers, this is used to minimize the cost function. Because the travel routes and meeting times do not follow a regular schedule, the pattern of PEV usage is different in comparison to any regular commute travel profile. The diurnal energy requirements for any PEV largely depend on its regular activities. To capture the usual activities of the available PEVs, two commercial data loggers were used inside each vehicle. The parameters of initial consideration included Vehicle Speed, Charge Status, Battery Level (% and Wh), Battery Voltage, Battery Current, Battery Temperature, Motor Torque, and Motor Speed. Travel patterns and profiles have been generated using the available parameters in combination with GPS tracking of the vehicle. As the charging characteristics cannot be inferred in real-time, hence they are translated from prior travel data and charging events. If any change in SOC occurred between turning on and off the vehicle, that can be evaluated using subsequent trip data (Yusuf et al., 2021). Fig. 3 shows the change in SOC per trip. Most of the trips involve short-distance travel for attending meetings and covering distances of 9.66 to 12.87 km for a round trip, so the resulting change in SOC is small. The maximum change in SOC observed on a few occasions is 22.5%. Fig. 4 shows the initial SOC before the trips were made. A total of 544 trips were made with the two light-duty PEVs from Nov 2018 to Oct 2019. Initial SOC mostly lies between 60-80% of the total capacity of the available PEVs.

3. Problem Formulation and Constraints

3.1. Problem Formulation

The goal is to minimize the overall cost of EV operation in any workplace-integrated microgrid having a similar infrastructure to this one. This overall cost includes the total cost of energy and battery degradation.

$$\text{minimize}\ (\text{Energy Cost} + \text{Battery Degradation Cost}) \tag{3}$$

3.2. Energy Cost

The first objective of this multi-objective problem is minimizing the cost of energy purchased from the grid. The total energy cost can be described by (4). Eq. (5) shows the sum of delivering power from the grid, solar, and EV is equal to the sum of power required by EV and the building. The total charging and discharging power by EV is calculated by (6) and (7). The EV SOC, charging, and discharging rates are constrained by (8)-(11). The charging and discharging decision variables are binary which are imposed by (12)-(13). for $\forall t \in T$, $\forall n_{ld} \in N_{ld}$, $\forall n_{hd} \in N_{hd}$, $\forall l_1 \in L_{ch}$, $\forall l_2 \in L_{disch}$,

$$\text{Energy Cost} = \sum_{t=1}^{T} P_{grid}(t) \times \Delta t \times C_e(t) \tag{4}$$

$$P_{grid}(t) + P_{EV,disch,total}(t) + P_{solar}(t) = P_{EV,ch,total}(t) + P_{building}(t) \tag{5}$$

$$P_{EV,ch,total}(t) = \sum_{\forall n_{ld} \in N_{ld}} A_{EV,n_{ld}}(t) \times P_{EV,ch,n_{ld}}(t) + \sum_{\forall n_{hd} \in N_{hd}} A_{EV,n_{hd}}(t) \times P_{EV,ch,n_{hd}}(t) \tag{6}$$

$$P_{EV,disch,total}(t) = \sum_{\forall n_{ld} \in N_{ld}} A_{EV,n_{ld}}(t) \times P_{EV,disch,n_{ld}}(t) + \sum_{\forall n_{hd} \in N_{hd}} A_{EV,n_{hd}}(t) \times P_{EV,disch,n_{hd}}(t) \tag{7}$$

$$\mathrm{SOC_{EV}}(t) = \mathrm{SOC_{EV}}(t-1) + \left\{ \left(\eta_{\mathrm{ch,\ EV}} \times P_{EV,ch}(t) - P_{EV,disch}(t) / \eta_{\mathrm{disch,EV}}\right) / Cap_{init} \right\} \times \Delta t \tag{8}$$

$$\mathrm{SOC_{min,EV}} \leq \mathrm{SOC_{EV}}(t) \leq \mathrm{SOC_{max,EV}} \tag{9}$$

$$0 \leq P_{EV,ch}(t) \leq l_1(t) \times P_{EV,ch\ \max} \tag{10}$$

$$0 \leq P_{EV,disch}(t) \leq l_2(t) \times P_{EV,disch\ \max} \tag{11}$$

$$l_1(t) + l_2(t) = 1 \tag{12}$$

$$l_1(t), l_2(t) \in \{0, 1\} \tag{13}$$

3.3. Battery Degradation Cost

The EV battery degradation depends on multiple factors such as temperature and operating conditions. The battery degradation cost can be described by the Eq. (14) (Ahmadian et al., 2018, Guenther et al., 2013). The impact of yearly degradation is highly dependent on the operating temperature and negligible in comparison to the cycle degradation. Hence, only cycle degradation is used to compute the daily battery degradation cost.

$$\text{Battery Degradation Cost} = \sum_{t=1}^{T} C_{battery} \times \frac{(Deg_{calendar} + Deg_{cycle})}{(Cap_{init} - Cap_{useful})} \tag{14}$$

$$Cap_{useful} = 0.8 \times Cap_{init} \tag{15}$$

$$Deg_{cycle} = a \times DOD^3 + b \times DOD^2 + c \times DOD \tag{16}$$

To make it quadratic and solve it by the off the shelf solvers like Gurobi (Gurobi Optimization, LLC, 2022) and improve the computation time, an auxiliary variable is introduced. If $y' = DOD^2$, then the above equation can be written as

$$Deg_{cycle} = a1 \times y' \times DOD + b \times y' + c \times DOD \tag{17}$$

3.4. Payback Period and Yearly Savings Analysis

The parameters for cost-benefit analysis and finding out the best combination of LDEV and HDEV are as follows. The selection between HDEV and LDEV can be chosen based on the parameters mentioned here. These two parameters will help the owners to decide the right trade-off for a combination of different types of EVs.

$$\text{Payback Period} = \frac{\textit{Total Operational and Installation Cost}}{\textit{Yearly Savings}} \tag{18}$$

$$\begin{aligned}&\textit{Total Operational and Installation Cost}\\ &= \text{Equipment cost} + \text{Installation cost} + \text{Annual recurring fees}\end{aligned} \tag{19}$$

$$\textit{Yearly Savings} = 365 \times \text{Daily savings from optimized EV operation} \tag{20}$$

3.5. Optimization

The cost function along with its constraints is a Mixed Integer Programming (MIP) and a non-convex problem. The optimization is done for 1-day operation that includes 24 hours of data equivalent to 96 timestamps. The problem is solved in the Gurobi optimization solver with a work station having i-7 core and 16 GB RAM (Gurobi

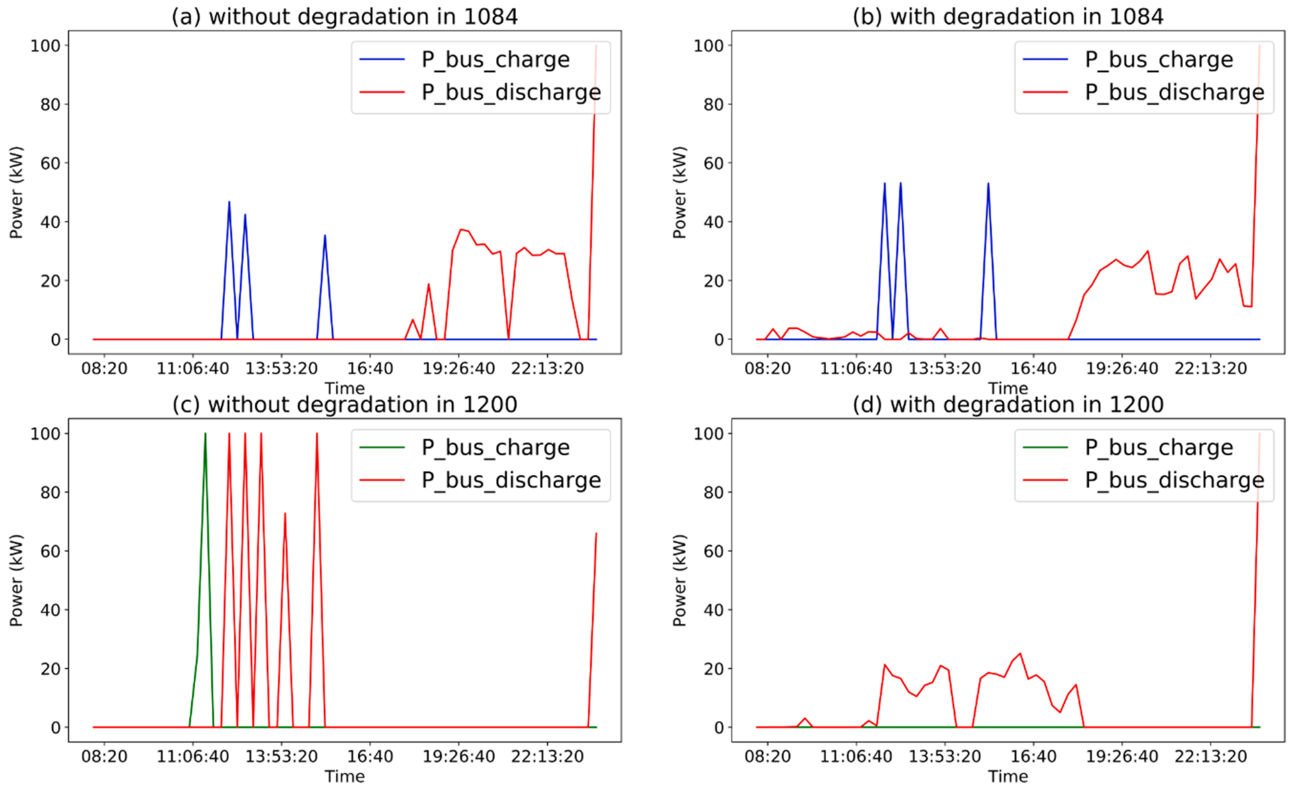

Fig. 5. Case I: HDEV activities in different buildings with off-board charging; HDEV was unavailable before 8.30 and between 14:00 and 15:00.

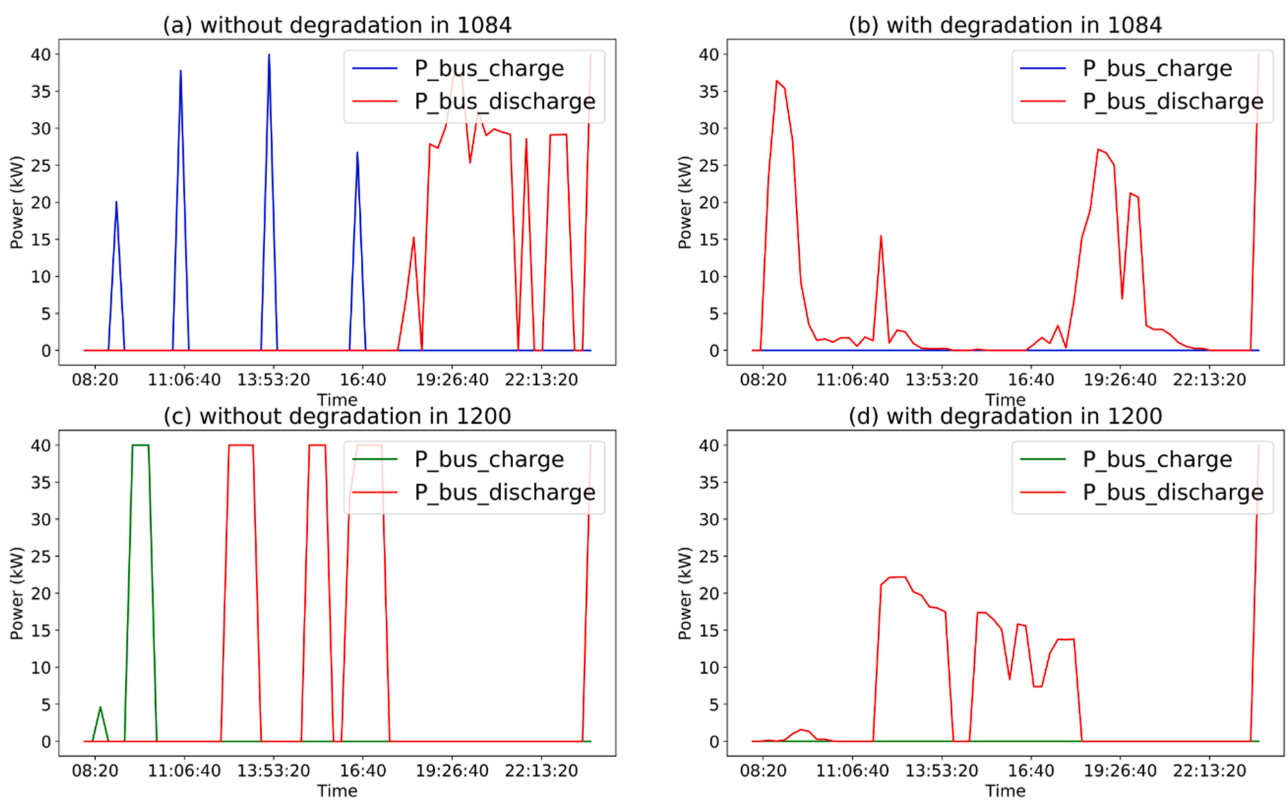

Fig. 6. Case I: HDEV activities in different buildings with on-board charging; HDEV was unavailable before 8.30 and between 14:00 and 15:00.

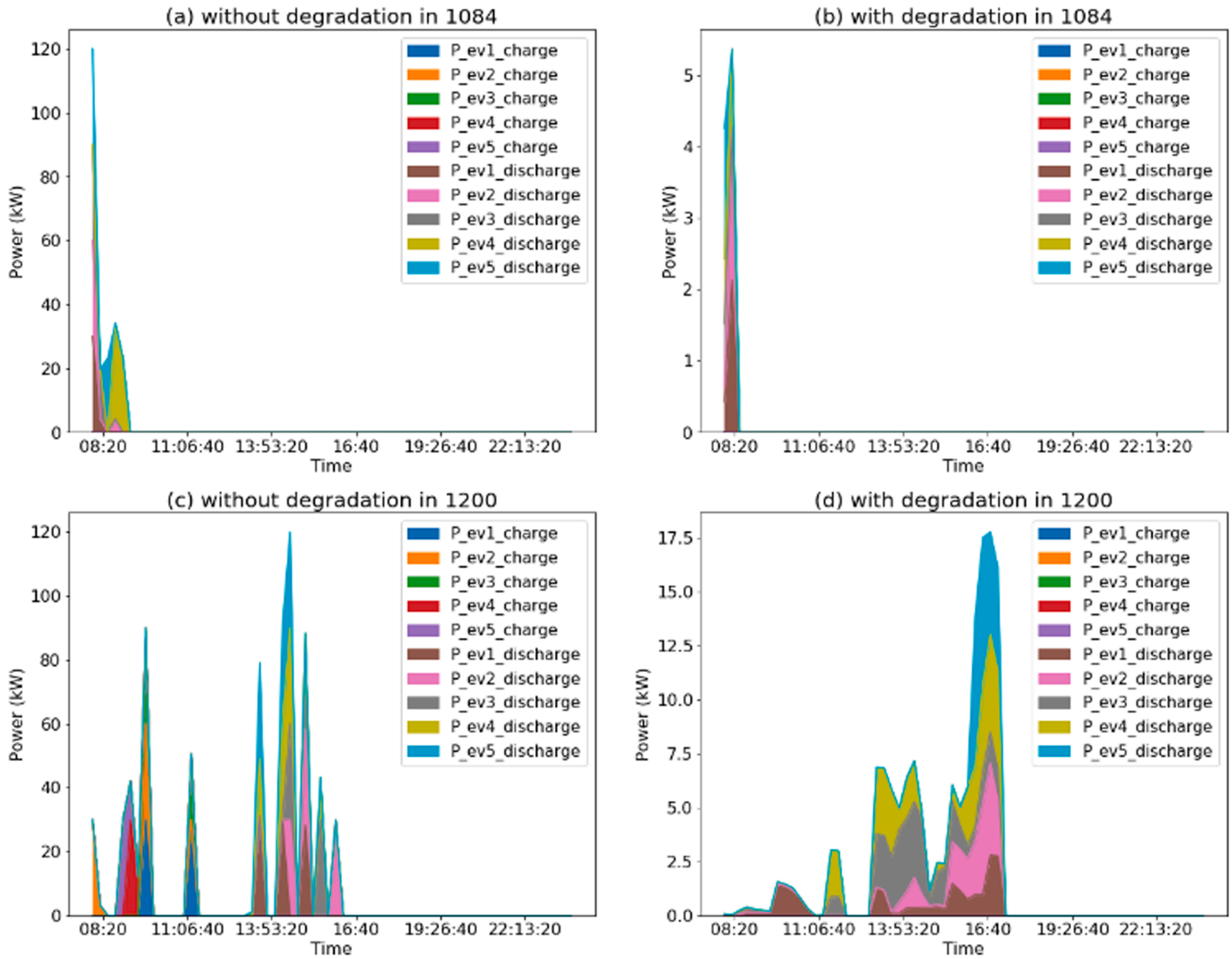

Fig. 7. Case II: LDEV activities in different buildings with off-board charging; LDEV was unavailable between 12:00 and 13:00; and after 17:00.

Optimization, LLC, 2022).

4. Results and Discussions

4.1. Optimal Scheduling of EVs

4.1.1. Case I: Only HDEV is present

The first case explores the opportunity for cost optimization by the electric trolley in this commercial building-integrated microgrid. The electric trolley is available for charging and discharging anytime outside the morning (before 8:30) and afternoon (between 14:00 and 15:00) scheduled trip times. Both 1084 and 1200 buildings are considered for this scenario and the cost opportunity is examined for both on-board and off-board charger activities. It is assumed that the on-board charger in the bus allows a maximum of 40 kW and the off-board charger allows a maximum of 100 kW for charging/discharging. Though the actual electric bus does not allow bidirectional charging with the on-board charger (40 kW), 100 kW bidirectional power transfer is possible through the inverter mounted on the mobile trailer. Figs. 5 and 6 show the grid-to-vehicle (G2V) and vehicle-to-grid (V2G) activities by the electric trolley on both of the buildings for different charger configurations, respectively. The 1084 building is enriched with surplus solar production during the daytime. Hence, the charging events take place when solar is available despite the on-peak hours (12 pm – 6 pm), and the bus discharges when solar goes down in the afternoon. Despite the capacity of charging at 100 kW rates, the HDEV charges slowly to balance the net power at 1084 building with off-board configurations. Though the solar is abundant from 14:00-15:00, no charging takes place due to the unavailability of the HDEV. During the late evening hours, the on-board charger triggers more discharging events due to its low discharging capacity of 40 kW. When degradation cost is included, a higher Depth of Discharge (DoD) leads to higher degradation. Hence, the bus charging/discharging activities are lower compared to the activities without the effort to minimize the degradation cost. The charging/discharging rates are also lower when the degradation cost is included. Solar production in the 1200 building is not enough to compensate for all the building loads. More discharging events take place during the day and the discharging rate is also maximum. The inclusion of degradation cost leads to a moderate charging/discharging profile for a longer period to extend the battery life.

4.1.2. Case II: Only LDEVs are present

LDEVs are assumed to be available for energy optimization in the second case. It is assumed that all the LDEVs are identical and the capacity of each is 40 kWh. All the off-board chargers are bidirectional and the maximum bidirectional capability of each charger is 30 kW. The on-board chargers in the LDEVs are assumed to be bidirectional and the power rating of 6.6 kW is representative of level II EV charging/discharging. The availability of LDEVs depends on the regular work schedules. They are unavailable during the lunch period (12- 1 pm) and out of work hours (after 5 pm). As Fig. 3 indicates that the maximum change of SOC level is 22.5 percent which only occurs rarely. In general, for this LDEV model with a 30 kWh/160.93 km rating, a round trip of 41.84 km can be completed if it has a comfortable SOC level at the

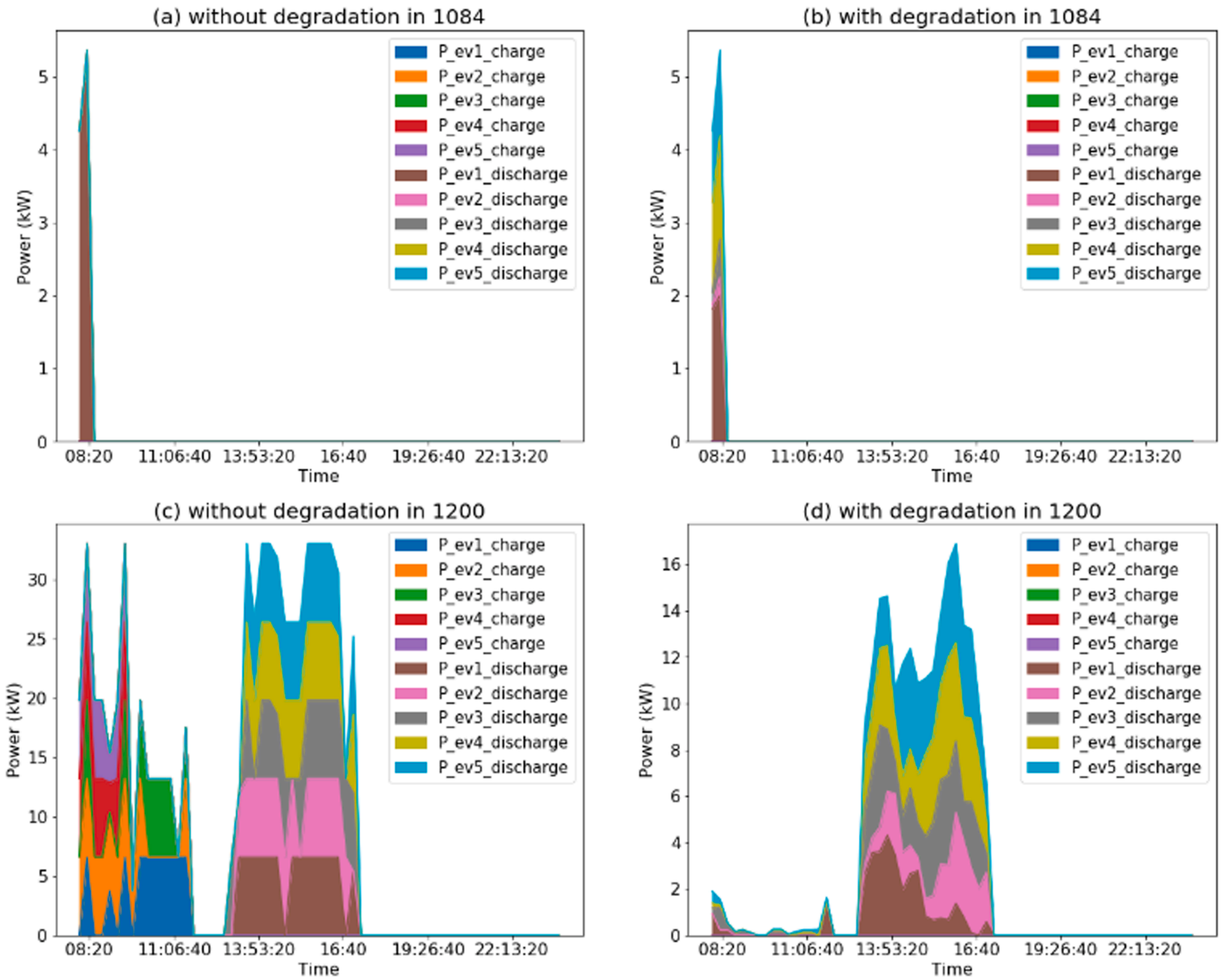

Fig. 8. Case II: LDEV activities in different buildings with on-board charging; LDEV was unavailable between 12:00 and 13:00; and after 17:00.

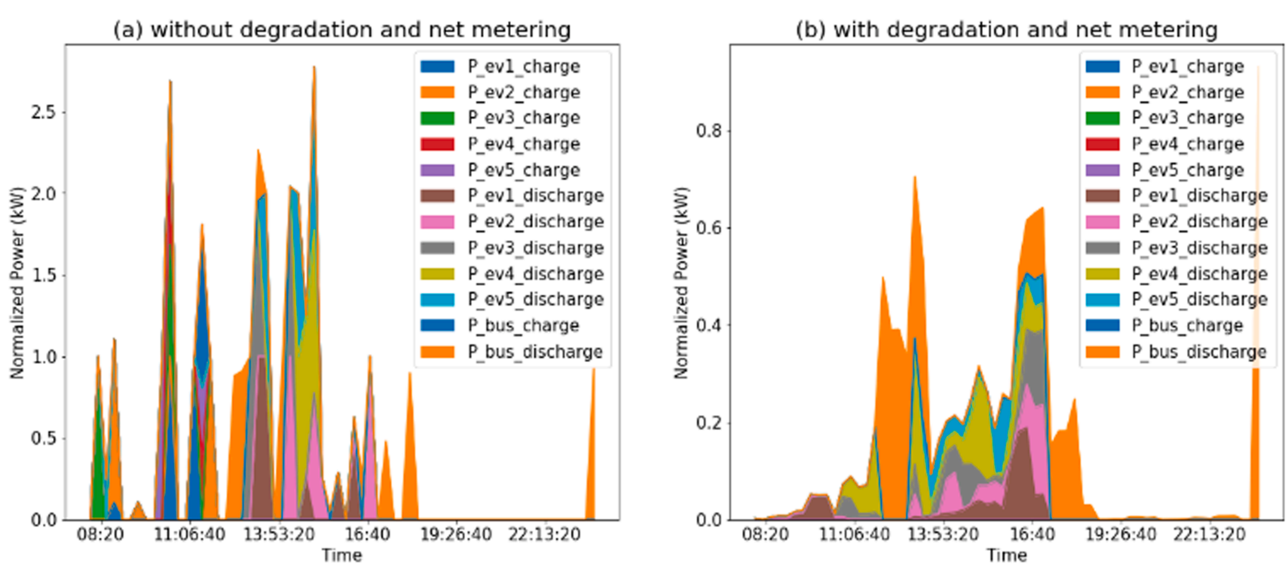

Fig. 9. Case III: LDEV and HDEV activities in different buildings with net metering and off-board charging.

starting and wants to finish the trip with 20 percent SOC left (Fuel Economy 2022). So, the minimum SOC level is assumed 40 percent of the total capacity to allow for the completion of the return trip.

The initial SOCs of all the LDEVs are chosen randomly and assumed to be 50-80% of the total SOC. The LDEVs start discharging in the early morning in the 1084 building. They follow the same characteristics with

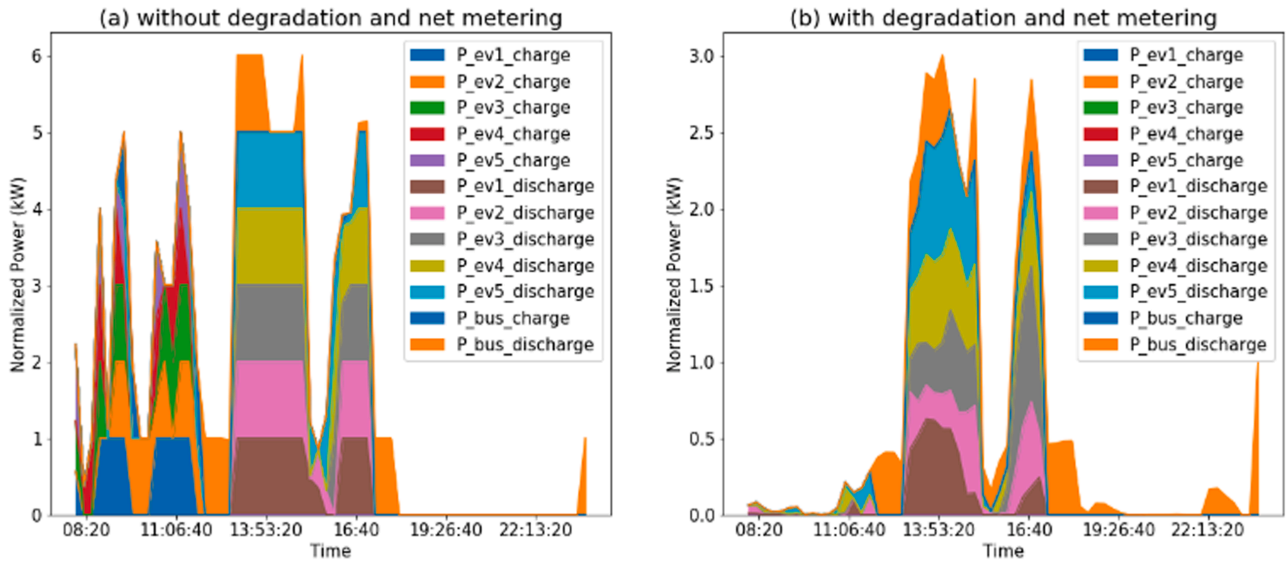

Fig. 10. Case III: LDEV and HDEV activities in different buildings with net metering and on-board charging.

Table 3
Time of use energy cost (Electric Rules & Rates 2022).

Time	Price ($/kWh)
Off-Peak (11 pm - 8 am)	0.0773
Mid-Peak (8 am -12 pm), (6 pm-11 pm)	0.0898
On-Peak (12 pm - 6 pm)	0.1104

the addition of the depreciation cost but discharge at slower rates to reduce the total number of battery cycling. When the solar is available in 1084 after early morning, there is no need to discharge the LDEVs. If all the LDEVs are connected to the 1200 building, they get charged in the early hours of the day when the electricity price is low to have more energy available for V2G activities when the electricity price is high. All the LDEVs take part in reducing the net load and the discharging rates are slower during the overall cost (energy cost+ battery degradation cost) optimization. For 1200 building, the maximum total discharging power reduces to approximately one-sixth of capable V2G in off-board configurations whereas the amount of reduction is nearly half for the on-board configurations with the inclusion of degradation cost as shown in Figs. 7 and 8. This shows that the V2G availability largely depends on the number of LDEVs in the fleets and their configurations.

4.1.3. Case III: Both LDEV and HDEV are present

The last case study includes both LDEVs and HDEVs for optimization with two scenarios: a) net metering and b) no net metering. Fig. 9 shows the optimal scheduling of LDEVs and HDEVs when all of them try to minimize the overall energy cost of two buildings. If net metering is available, then it is possible to optimize the net load by the LDEVs and HDEV. The presence of net metering helps to utilize the curtailed solar energy of the 1084 building. The LDEVs also discharge and utilize their remaining energy during the on-peak hours. The degradation cost constraint leads to the controlled lower discharging rates of the vehicles to conserve battery life. Fig. 10 shows the LDEVs and HDEV activities with on-board charger configurations.

4.2. Cost Savings

The regular energy cost without any EV is calculated for the buildings where the Time of Use (TOU) energy rate shown in Table 3 is applied. The energy costs for the buildings along with the uncoordinated LDEV and HDEVs are also calculated. When implementing uncoordinated EV charging, it means that all the EVs start charging when they are plugged in regardless of the TOU energy rates or the availability of solar energy. They recharge again after any trip that happened during the day to make up for the used energy. Table 4 and Table 5 show the cost savings for off-board and on-board configurations in comparison to the no EV and uncoordinated EV cases, respectively. The electric trolley provides the maximum cost saving opportunity due to its availability at night time and fixed number of trips. LDEVs generate lower savings due to their fixed presence at the worksite and are unavailable after 5 pm. Net metering always provides higher savings in comparison to no net metering. The inclusion of degradation cost reduces the amount of savings. The cost savings don't vary much and do

Table 4
Cost savings for off-board EVSE.

Cases	Building	No EV and with Optimization		EV Uncoordinated and Coordinated	
		No degradation	degradation	No degradation	degradation
Case I	1084	73.9%	42.1%	79.3%	54.1%
	1200	7.2%	5.2%	10.4%	8.6%
Case II	1084	1.5%	-	35.2%	34.3%
	1200	4.2%	-	9.4%	5.4%
Case III	net metering	13.2%	5.8%	21.6%	14.9%
	no net metering	6.7%	4.8%	13.4%	11.7%

Table 5
Cost savings for on-board EVSE.

Cases	Building	No EV and Optimization		Uncoordinated and Coordinated	
		No degradation	degradation	No degradation	degradation
Case I	1084	73.9%	11.2%	79.3%	29.6%
	1200	6.8%	4.9%	10.1%	8.3%
Case II	1084	1.5%	-	35.2%	34.3%
	1200	4.2%	-	9.4%	5.5%
Case III	net metering	12.4%	5.5%	20.9%	14.6%
	no net metering	6.4%	4.5%	13.2%	11.4%

Table 6
Peak reduction with optimized operation.

Cases	Building Number	Off-board No degradation	Off-board degradation	On-board No degradation	On-board degradation
Case I	1084	67.2%	79.6%	16.5%	17.9%
	1200	15.2%	35.4%	12.2%	18.0%
Case II	1084	75.8%	75.8%	2.6%	2.6%
	1200	26.2%	44.7%	0.0%	15.5%
Case III	net metering	34.8%	43.8%	19.5%	24.3%
	no net metering	36.6%	49.6%	10.8%	15.7%

Table 7
Cost of EVCS Equipment (Mass DOER Electric School Bus Pilot Project Evaluation 2022).

Type	On-board ($)	Off-board ($)
Charging Infrastructure	25,000	60,000
Installation per site	10,000	10,000
Vehicle upgrades	12,000	8,000

Table 8
Payback Period in Years for Off-board EVSE.

Cases	Building Number	No EV and EV No degradation	No EV and EV degradation	Uncontrolled vs Optimized No degradation	Uncontrolled vs Optimized degradation
Case I	1084	1.59	2.80	1.18	1.73
	1200	1.54	2.11	1.02	1.24
Case II	1084	320.25	-	8.75	8.98
	1200	10.53	-	4.43	7.65
Case III	net metering	4.60	10.39	2.54	3.67
	no net metering	7.34	10.20	3.38	3.88

Table 9
Payback Period in Years for On-board EVSE.

Cases	Building Number	No EV and EV No degradation	No EV and EV degradation	Uncontrolled vs Optimized No degradation	Uncontrolled vs Optimized degradation
Case I	1084	0.96	6.31	0.71	1.90
	1200	0.97	1.35	0.63	0.77
Case II	1084	139.47	-	3.81	3.91
	1200	4.59	-	1.93	3.31
Case III	net metering	2.22	5.02	1.19	1.71
	no net metering	3.49	4.93	1.57	1.80

not depend on charger configurations (i.e., on-board or off-board). Higher savings are more likely in regular commercial buildings like 1084 and net metering provides the highest cost benefit for the off-board charger configurations. Between 1.5% to 79.3% cost saving is possible depending on the EV operation strategy and overall system infrastructure (building load, vehicle spec, availability of vehicles). It is noted that no savings are possible with LDEVs compared to no EV situation when degradation cost is added.

4.3. Peak Reduction

Table 6 shows the change in peaks for optimized operation in comparison to uncoordinated EV charging. Off-board configuration provides higher peak reduction compared to on-board configurations. The inclusion of degradation cost leads to higher peak savings in almost all cases. The capability of reducing the peak in the 1200 building is lower for off-board chargers. Net metering provides a higher peak reduction for on-board or level II charging capabilities in comparison to no net metering available. Between 2.6% to 79.6% peak reduction is possible depending on the system infrastructure.

4.4. Payback Period

The payback period is another important parameter for the building owners to make decisions on EV infrastructure investments. Table 7 shows the cost of different EVCS equipment for various charger configurations.

The payback periods for all the cases are tabulated in Table 8 and Table 9. It is possible to reach break-even in 1.24 years in building 1200 for case I with off-board configurations. A maximum of 9 years are required for case II whereas 3.88 years are needed to get the initial investment back for the net metering scenario.

On the other hand, less time is required with on-board charger configurations to make a profit. It takes less than a year to make a profit in case I and a maximum of 4 years to make a profit in case II. Almost 2 years are needed in case III which is almost half compared to case III off-board configurations.

4.5. Impacts of Fleet Size

The size of the fleet is an important factor as well to invest in the EV infrastructure. Hence, the current EV penetration scenario is compared with 10 and 20 percent EV parking spaces penetration scenarios, respectively. The maximum number of EV parking spaces can be 200 for the size of this type of infrastructure (Parking & Loading Standards, 2022) and the HDEV and LDEV mix ratio is considered 30 and 70 percent (Light-Duty Vehicles Accounted for the Majority of Transportation Energy Consumption, 2022). Fig. 11 shows the payback period for these different scenarios when net metering is available, and degradation is not considered. Though the payback period reduces when the penetration increases, the optimal payback period can be achieved when 10 percent of the parking spaces get penetrated with PEV.

5. Conclusions and Future Work

The real time implementation of smart bidirectional HDEV and LDEV charging strategies exemplifies both challenges and opportunities. In this paper, a data-driven innovative framework is introduced, followed by a MIP model to minimize the overall cost of two different commercial buildings. This framework will help the building owners to take decisions on necessary investments for charging infrastructures and plan accordingly. Later on, an extensive cost-benefit analysis was completed in terms of charger configurations, payback periods, energy cost savings, and peak reductions. For this specific case, the findings show that it is more economical to have an HDEV with fixed travel schedules for energy savings. The least payback period is possible by deploying an HDEV in a large energy user building. Net metering always helps to get the initial investment back in a shorter period. The inclusion of degradation cost results in better peak reductions. This case study can be replicated in any university campus in the U.S. having similar settings. As this university campus has a large parking area, it is possible to accommodate more HDEVs and LDEVs. Implementing the proposed framework for a larger setting can be used as a base case for other large commercial building owners. The long-term operation of this setting to explore the impacts of seasonality and the integration of OpenADR (Connecting Smart Energy to the Grid, 2022) for utilities are some of the possible cases worth investigating in the future.

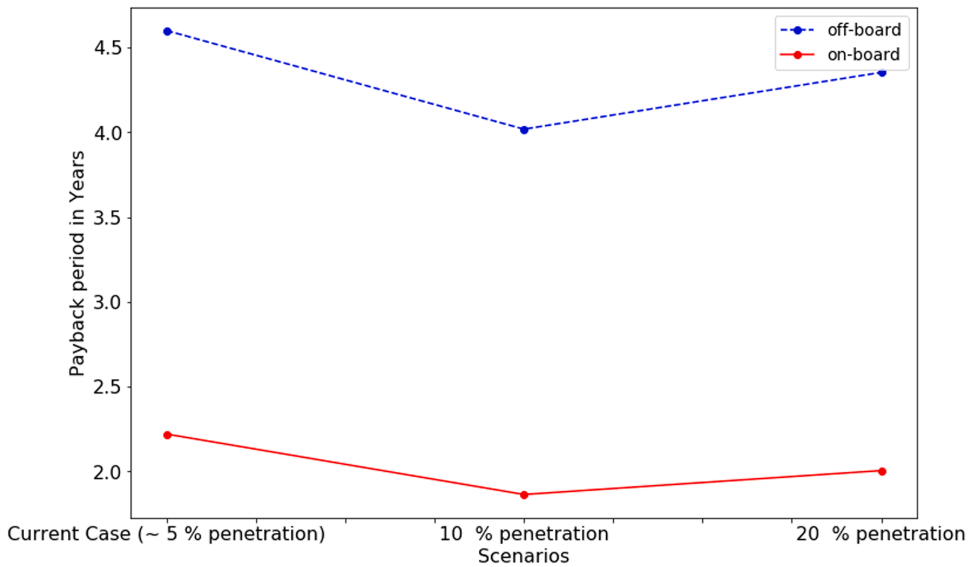

Fig. 11. Impacts of Fleet Size on Payback Period for Net Metering.

Table A
Daily base cost for the buildings.

Cases	Building Number	Daily Electricity Cost ($)	Daily Electricity Cost+ EV Charging Cost ($)
Case I	1084	15.12	19.06
	1200	161.2	167.12
Case II	1084	15.12	22.99
	1200	161.2	170.45
Case III	net metering	142.34	157.52
	no net metering	176.32	190.11

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix

Table A

References

Ahmadian, A, Sedghi, M, Elkamel, A, Fowler, M, & Golkar, MA (2018). Plug-in electric vehicle batteries degradation modeling for smart grid studies: Review, assessment and conceptual framework. *Renewable and Sustainable Energy Reviews, 81*(2), 2609–2624. https://doi.org/10.1016/j.rser.2017.06.067. Part.

Bagheri Tookanlou, M., Marzband, M., Al Sumaiti, A., & Mazza, A. (2020). Cost-benefit analysis for multiple agents considering an electric vehicle charging/discharging strategy and grid integration. In *20th IEEE Mediterr. Electrotech. Conf. MELECON 2020 - Proc* (pp. 19–24). https://doi.org/10.1109/MELECON48756.2020.9140637

Basma, H., Mansour, C., Nemer, M., Haddad, M., & Stabat, P. (2020). Optimization of battery electric bus charging under varying operating conditions. In *2020 IEEE Vehicle Power and Propulsion Conference*. VPPC. https://doi.org/10.1109/VPPC49601.2020.9330838. - Proceedings.

Beekman, R., & Van Den Hoed, R. (2016). Operational demands as determining factor for electric bus charging infrastructure. *IET Conference Publications*, (CP691), 1–6. https://doi.org/10.1049/cp.2016.0963

Brinkel, N. B. G., Schram, W. L., AlSkaif, T. A., Lampropoulos, I., & van Sark, W. G. J. H. M. (2020). Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits. *Applied Energy, 276*(April), Article 115285. https://doi.org/10.1016/j.apenergy.2020.115285

California Targets Nearly $400M to Fill Gaps in EV Charging Infrastructure [Cited 2022] Available from: https://www.greentechmedia.com/articles/read/california-targets-384m-to-fill-gaps-in-electric-vehicle-charging-infrastructure.

Chen, H., Hu, Z., Xu, Z., Li, J., Zhang, H., Xia, X., Ning, K., & Peng, M. (2016). Coordinated charging strategies for electric bus fast charging stations. In *Asia-Pacific Power and Energy Engineering Conference, APPEEC, 2016-Decem* (pp. 1174–1179). https://doi.org/10.1109/APPEEC.2016.7779677

Cheng, P. H., Huang, T. H., Chien, Y. W., Wu, C. L., Tai, C. S., & Fu, L. C. (2020). Demand-side management in residential community realizing sharing economy with bidirectional PEV while additionally considering commercial area. *International Journal of Electrical Power & Energy Systems, 116*, Article 105512. https://doi.org/10.1016/j.ijepes.2019.105512. ISSN 0142-0615.

Chollet at el, F. (2015). *Keras*. Github [Cited 2022] Available from: https://github.com/fchollet/keras.

Connecting Smart Energy to the Grid [Cited 2022] Available from: https://www.openadr.org.

Corinaldesi, C., Lettner, G., & Auer, H. (2022). On the characterization and evaluation of residential on-site E-car-sharing. *Energy, 246*, Article 123400. https://doi.org/10.1016/j.energy.2022.123400. ISSN 0360-5442.

David, A. O., & Al-Anbagi, I. (2017). EVs for frequency regulation: Cost benefit analysis in a smart grid environment. *IET Electr. Syst. Transp., 7*(4), 310–317. https://doi.org/10.1049/iet-est.2017.0007

Electric Rules & Rates [Cited 2022] Available from: https://www.riversideca.gov/utilities/businesses/rates/electric-rules-rates.

Fan, J., & Chen, Z. (2019). Cost-Benefit Analysis of Optimal Charging Strategy for Electric Vehicle with V2G. In *51st North Am. Power Symp. NAPS 2019* (pp. 1–6). https://doi.org/10.1109/NAPS46351.2019.9000391

Fanti, M. P., Mangini, A. M., Roccotelli, M., & Silvestri, B. (2022). Innovative Approaches for Electric Vehicles Relocation in Sharing Systems. *IEEE Transactions on Automation Science and Engineering, 19*(1), 21–36. https://doi.org/10.1109/TASE.2021.3103808. Jan.

Firouzjah, KG (2022). A Techno-Economic Energy Management Strategy for Electric Vehicles in Public Parking Lot Considering Multi-Scenario Simulations. *Sustainable Cities and Society, 81*, Article 103845. https://doi.org/10.1016/j.scs.2022.103845. ISSN 2210-6707.

Fuel Economy [Cited 2022] Available from: https://www.fueleconomy.gov/feg/Find.do?action=sbs&id=40812.

Gormez, M. A., Haque, E., & Sozer, Y. (2021). Cost optimization of an opportunity charging bus network. *IEEE Transactions on Industry Applications, 9994*(c). https://doi.org/10.1109/TIA.2021.3061031

Guenther, C, Schott, B, Hennings, W, Waldowski, P, & Danzer, MA. (2013). Model-based investigation of electric vehicle battery aging by means of vehicle-to-grid scenario simulations. *Journal of Power Sources, 239*, 604–610. https://doi.org/10.1016/j.jpowsour.2013.02.041

Gurobi Optimization, LLC, "Gurobi Optimizer Reference Manual" [Cited 2022] Available from: https://www.gurobi.com.

Heredia, W. B., Chaudhari, K., Meintz, A., Jun, M., & Pless, S. (2020). Evaluation of smart charging for electric vehicle-to-building integration: A case study. *Applied Energy, 266*(November 2019), Article 114803. https://doi.org/10.1016/j.apenergy.2020.114803

Houbbadi, A., Trigui, R., Pelissier, S., Bouton, T., & Redondo-Iglesias, E. (2018). Multi-objective optimisation of the management of electric bus fleet charging. In *2017 IEEE Vehicle Power and Propulsion Conference, VPPC 2017 - Proceedings* (pp. 1–6). https://doi.org/10.1109/VPPC.2017.8331015. -Janua.

Hu, Q., Bu, S., & Terzija, V. (2021). A Distributed P and Q Provision-Based Voltage Regulation Scheme by Incentivized EV Fleet Charging for Resistive Distribution Networks. *IEEE Transactions on Transportation Electrification, 7*(4), 2376–2389. https://doi.org/10.1109/TTE.2021.3068270. Dec.

Jiang, M., Zhang, Y., Zhang, C., Zhang, K., Zhang, G., & Zhao, Z. (2018). Operation and scheduling of pure electric buses under regular charging mode. In *IEEE Conference on Intelligent Transportation Systems, Proceedings* (pp. 1894–1899). ITSC. https://doi.org/10.1109/ITSC.2018.8569667. -Novem.

Kampker, A., Pandey, R., Gomez, J. G. D., Wessel, S., Treichel, P. E., & Malatyali, I. (2019). Cost optimal design strategy of electric drivetrains for medium heavy-duty vehicles based on product development and production costs. In *2019 9th International Electric Drives Production Conference*. EDPC. https://doi.org/10.1109/EDPC48408.2019.9011844. - Proceedings.

Kingma, DP, & Ba, J (2017). Adam: A Method for Stochastic Optimization. *arXiv: 1412.6980*.

Koubaa, R., Yoldas, Y., Goren, S., Krichen, L., & Onen, A. (2020). Implementation of cost benefit analysis of vehicle to grid coupled real Micro-Grid by considering battery energy wear: Practical study case. *Energy Environ*. https://doi.org/10.1177/0958305X20965158

Light-Duty Vehicles Accounted for the Majority of Transportation Energy Consumption [Cited 2022] Available from: https://www.energy.gov/eere/vehicles/articles/fotw-1072-march-11-2019-light-duty-vehicles-accounted-majority-transportation.

Luo, Z., Hu, Z., Song, Y., Xu, Z., & Lu, H. (2013). Optimal Coordination of plug-in electric vehicles in power grids with cost-benefit analysis—part I: Enabling techniques. *IEEE Transactions on Power Systems, 28*(4), 3546–3555. https://doi.org/10.1109/TPWRS.2013.2262318. Nov.

Luo, Z., Hu, Z., Song, Y., Xu, Z., & Lu, H. (2013). Optimal coordination of plug-in electric vehicles in power grids with cost-benefit analysis - Part II: A case study in China. *Ieee Transactions on Power Systems, 28*(4), 3556–3565. https://doi.org/10.1109/TPWRS.2013.2252028

Mass DOER Electric School Bus Pilot Project Evaluation [Cited 2022] Available from: https://www.mass.gov/doc/mass-doer-electric-school-bus-pilot-project-evaluation.

Moradipari, A., Tucker, N., Zhang, T., Cezar, G., & Alizadeh, M. (2020). Mobility-aware smart charging of electric bus fleets. In *IEEE Power and Energy Society General Meeting*. https://doi.org/10.1109/PESGM41954.2020.9281897. -Augus.

Nissan Leaf [Cited 2022] Available from: https://www.nissanusa.com/vehicles/electric-cars/leaf.html?dcp=psn.58700004660019373&ds_rl=1253905&gclid=EAIaIQobChMIxf7A1OLu6AIVjeNkCh2p8Ai1EAAYASAAEgIXcvD_BwE&gclsrc=aw.ds.

Oda, T., Aziz, M., Mitani, T., Watanabe, Y., & Kashiwagi, T. (2018). Mitigation of congestion related to quick charging of electric vehicles based on waiting time and cost–benefit analyses: A japanese case study. *Sustain. Cities Soc., 36*(June 2017), 99–106. https://doi.org/10.1016/j.scs.2017.10.024

Pan, J., Wu, X., Feng, Q., & Ji, Y. (2020). Optimization of electric bus charging station considering energy storage system. In *2020 8th international conference on power electronics systems and applications: Future mobility and future power transfer*. PESA. https://doi.org/10.1109/PESA50370.2020.9343999.

Parking and Loading Standards [Cited 2022] Available from: https://www.codepublishing.com/CA/Galt/html/Galt18/Galt1848.html.

Qureshi, KN, Alhudhaif, A, & Jeon, G (2021). Electric-vehicle energy management and charging scheduling system in sustainable cities and society. *Sustainable Cities and Society, 71*, Article 102990. https://doi.org/10.1016/j.scs.2021.102990. ISSN 2210-6707.

Riverside Transit Agency [Cited 2022] Available from: https://www.riversidetransit.com/.

Rodríguez-Molina, J., Castillejo, P., Beltran, V., & Martínez-Núñez, M. (2020). A Model for Cost–Benefit Analysis of Privately Owned Vehicle-to-Grid Solutions. *Energies, 13* (21), 5814. https://doi.org/10.3390/en13215814

Singh, J., & Tiwari, R. (2020). Cost Benefit Analysis for V2G Implementation of Electric Vehicles in Distribution System. *Ieee Transactions on Industry Applications, 56*(5), 5963–5973. https://doi.org/10.1109/TIA.2020.2986185

Sufyan, M., Rahim, N. A., Muhammad, M. A., Tan, C. K., Raihan, S. R. S., & Bakar, A. H. A. (2020). Charge coordination and battery lifecycle analysis of electric vehicles with V2G implementation. *Electric Power Systems Reserch, 184*(March), Article 106307. https://doi.org/10.1016/j.epsr.2020.106307

Tamura, S. (2020). A V2G strategy to increase the cost–benefit of primary frequency regulation considering EV battery degradation. *Electr. Eng. Japan (English Transl. Denki Gakkai Ronbunshi), 212*(1–4), 11–22. https://doi.org/10.1002/eej.23270

Transportation Electrification [Cited 2022] Available from: https://www.cpuc.ca.gov/zev/.

Ula, S, Yusuf, J, & Hasan, ASMJ (2019). Development and Deployment of an Integrated Microgrid Incorporating Solar PV, Battery Energy Storage and EV Charging. In *Conference Proceedings of Applied Energy Symposium: MIT A+B, vol. 1, Boston, MA*.

Wu, X, Freese, D, Cabrera, A, & Kitch, WA. (2015). Electric vehicles' energy consumption measurement and estimation. *Transportation Research Part D: Transport and Environment, 34*, 52–67. https://doi.org/10.1016/j.trd.2014.10.007

Yan, Q., Zhang, B., & Kezunovic, M. (2019). Optimized operational cost reduction for an EV charging station integrated with battery energy storage and PV generation. *Ieee Transactions on Smart Grid, 10*(2), 2096–2106. https://doi.org/10.1109/TSG.2017.2788440

Yang, M., Zhang, L., & Dong, W. (2020). Economic Benefit Analysis of Charging Models Based on Differential Electric Vehicle Charging Infrastructure Subsidy Policy in China. *Sustain. Cities Soc., 59*(April), Article 102206. https://doi.org/10.1016/j.scs.2020.102206

Yusuf, J., Watanabe, R., Ula, S., Todd, M., & Gomez, H. (2021). Data Driven Stochastic Energy Cost Optimization with V2G Operation in Commercial Buildings. In *2020 52nd North American Power Symposium (NAPS)* (pp. 1–6). https://doi.org/10.1109/NAPS50074.2021.944978

Yusuf, J., Faruque, R. B., Hasan, A. S. M. J., & Ula, S. (2019). Statistical and Deep Learning Methods for Electric Load Forecasting in Multiple Water Utility Sites. In *2019 IEEE Green Energy and Smart Systems Conference (IGESSC)* (pp. 1–5). https://doi.org/10.1109/IGESSC47875.2019.9042393

Zahedmanesh, A., Muttaqi, K. M., & Sutanto, D. (2021). A cooperative energy management in a virtual energy hub of an electric transportation system powered by PV generation and energy storage. *IEEE Transactions on Transportation Electrification, 7782*(c), 1–11. https://doi.org/10.1109/TTE.2021.3055218

Zhang, C. (2019). Charging schedule optimization of electric bus charging station considering departure timetable. *IET Conference Publications*, (CP764), 1–5. https://doi.org/10.1049/cp.2019.0606

Zhou, Y., Liu, C. X., Wei, R., & Golub, A. (2021). Bi-objective optimization for battery electric bus deployment considering cost and environmental equity. *IEEE Transactions on Intelligent Transportation Systems, 22*(4), 2487–2497. https://doi.org/10.1109/TITS.2020.3043687