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Sustainable Strategies for Energy Management in Buildings and Electric Vehicle Charging

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ABSTRACT

This study investigates the integration of electric vehicle (EV) charging stations into buildings as a sustainable strategy to reduce greenhouse gas emissions and promote clean energy adoption. While this initiative offers significant environmental advantages, it also introduces challenges such as high installation costs, the need for electrical infrastructure upgrades, and potential power quality concerns. To address these issues, the research utilizes Pareto frontier analysis and multi-objective optimization (MOO) techniques to identify optimal trade-offs among key objectives, including cost, energy efficiency, and system reliability. Three strategies (A, B, and C) are assessed, with Strategy C emerging as the most balanced and cost-effective option. The findings underscore the importance of prioritizing both economic viability and operational efficiency in decision-making processes. Overall, integrating EV charging stations into buildings demonstrates considerable potential as a step toward sustainability. However, a thorough evaluation of all influencing factors is critical to ensuring long-term success and alignment with global environmental goals.

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1. INTRODUCTION

Nowadays, energy management and optimizing energy usage have become the most important sector in different scales such as residential [1],[2]. Energy plays a crucial role in modern society, driving economic growth and improving living standards [3]. However, the methods of energy production and consumption have significant environmental impacts [4], [5]. Fossil fuels, while providing a substantial portion of our energy needs, contribute to air and water pollution, greenhouse gas emissions, and climate change [6]. Conversely, renewable energy sources like solar, wind, and hydroelectric power offer sustainable alternatives that reduce environmental harm [5]. Transitioning to cleaner energy not only mitigates ecological degradation but also promotes public health and enhances energy security, making it vital for a sustainable future [7].

Electric vehicles (EVs) are experiencing a surge in popularity as a sustainable and environmentally friendly mode of transportation [8]. According to the International Energy Agency (IEA), the global stock of EVs reached 11.2 million in 2020, a significant increase from 7.2 million in 2019, and is projected to reach 145 million by 2030. However, one of the primary challenges faced by EV owners is the availability of convenient and reliable charging infrastructure which is connected to power systems [9]. This is where buildings can play a crucial role by providing EV charging stations for their residents, employees, or visitors [10]. One of the key benefits of connecting buildings to EV charging stations is the potential to enhance the attractiveness and value of the buildings. For instance, residential buildings that offer EV charging stations can attract more tenants who own or plan to purchase EVs, leading to increased satisfaction and loyalty [11].

About 68% of EV owners in the United States consider access to home charging as a critical factor in their purchase decision. Similarly, commercial buildings that provide EV charging stations can attract more customers and employees who prefer driving EVs, thereby bolstering their reputation and brand image [12]. A study conducted by the Rocky Mountain Institute estimated that workplace charging could increase EV adoption by 6% to 24% by 2030. Moreover, connecting buildings to EV charging stations can contribute to the reduction of greenhouse gas emissions and energy consumption by utilizing renewable energy sources or employing smart grid technologies to power the charging stations [13]. This aligns with the sustainability goals of buildings and promotes compliance with environmental regulations. For example, the European Union has set a target of installing at least one recharging point per ten EVs by 2025 [14]. However, connecting buildings to EV charging stations also entails challenges and complexities. One of the primary challenges is the high cost and intricacy associated with installing and maintaining the charging infrastructure. Building owners may need to upgrade their electrical infrastructure, obtain necessary permits and approvals, and bear the expenses of electricity and maintenance fees. The installation cost of a public charging station in the United States can range from \$300 to \$50,000, depending on factors such as station type, power capacity, and location. Another challenge lies in the potential impact of charging stations on the power quality and reliability of buildings. Charging stations can lead to voltage fluctuations, harmonics, or power outages, particularly during peak demand periods. These issues can affect the performance and safety of electrical equipment and appliances within the buildings [15]. One of the primary challenges is the high upfront cost of installing EV charging stations and the challenge includes the cost of purchasing and installing the charging equipment, as well as any necessary site upgrades. For buildings that require significant electrical infrastructure upgrades, such as new wiring or transformers, these costs can be substantial [16]. Integrating EV charging stations often necessitate extensive electrical upgrades to the building, which can include enhancing the capacity of the building's electrical system, installing new circuit breakers, and potentially upgrading transformers. These upgrades are essential to ensure the building can handle the increased electrical load from multiple EV charging stations without compromising safety or reliability. The addition of EV charging stations can lead to power quality issues within the building's electrical system. This includes problems such as voltage fluctuations, harmonic distortions, and increased peak demand, which can affect the overall stability and efficiency of the building's power supply. Addressing these issues may require the installation of power quality improvement devices and ongoing monitoring.

According to a study by the Electric Power Research Institute, the peak load from EV charging is projected to increase by 38% by 2030, necessitating additional investments in grid infrastructure. To address these challenges, the adoption of best practices and solutions for connecting buildings to EV charging stations is crucial. Conducting feasibility studies and demand analyses before installation is one such best practice. This enables buildings to determine the optimal number, type, and placement of charging stations based on factors like available space, budget, and projected usage. Implementing a smart charging system is another effective approach, as it allows for the monitoring and control of the charging process, optimizing power distribution and consumption. This mitigates power quality and reliability issues while reducing electricity costs and emissions. Smart charging solutions include vehicle-to-grid (V2G), vehicle-to-building (V2B), and vehicle-to-home (V2H) technologies, enabling EVs to communicate and exchange power with the grid, building, or home, respectively. According to the IEA, smart charging has the potential to decrease the peak load from EV charging by 40% to 60% by 2030. Connecting buildings to EV charging stations presents numerous benefits and challenges. By embracing the best practices and innovative solutions, buildings can contribute to the widespread adoption of EVs, enhance their value, reduce greenhouse gas emissions, and promote sustainable transportation. As the global demand for EVs continues to rise, it is imperative to prioritize the development of robust charging infrastructure within buildings to support the growth of this transformative technology [17].

The authors in [18], created an advanced bi-level building management system that allows electric car scheduling and optimal temperature control in smart buildings. This system satisfies a variety of needs, including demand response and electric vehicle charging, while efficiently minimizing costs. It provides a thorough model for charging electric vehicles that accounts for particular charging station specifications as well as three-phase unbalanced systems. Furthermore, the system has a dispersed strategy to maximize fan coil management, allowing for accurate room temperature regulation. Comprehensive testing at the Savona Campus has produced excellent results, including a 20% daily cost decrease when compared to a basic heuristic approach. In addition, the system can save up to 35% by utilizing its response capabilities. The authors in [19], examined an electric vehicle (EV) charging system in a typical Malaysian home that is powered by building-integrated photovoltaic (BIPV) technology. Three different BIPV systems with different battery storage capacities were created and evaluated. The energy output for the year varied between 7.19 and 8.05 MWh. With the greatest savings in greenhouse gas (GHG) emissions 137,321,924 kg CO_2 and the lowest levelized cost of electricity (LCOE) was the grid-connected system without batteries. Genetic algorithms can be used to optimize the cost of electric vehicle production [20].

A decision model for energy sharing between an electric vehicle (EV) charging station and a building was presented in [21]. To balance energy demand, the model makes use of vehicle-to-building (V2B) and vehicle-to-grid (V2G) integration. The study analyzes the economic effectiveness of the V2G/V2B integration while considering a variety of driving behaviors and building categories. The study's conclusions offer insightful advice for creating intelligent communities and suggest the best integration techniques. In order to improve building energy management and power supply reliability, the authors in [22] investigated the integration of smart buildings and plug-in hybrid electric vehicles (PHEVs) using particle swarm optimization (PSO) and multi-agent technology. The primary goal is to reduce power consumption and increase customer comfort. Combining PHEVs allows the system to take advantage of their combined energy and capacity, which enhances the building's operational and financial stability. To verify that their suggested method works, the researchers run simulations and case studies. Robledo et al. presented a demonstration project conducted in the Netherlands, focusing on achieving a net-zero energy residential building [23]. It combines building-integrated photovoltaic (BIPV) solar panels and a hydrogen fuel cell electric vehicle (FCEV) in a vehicle-to-grid (V2G) operation. The project evaluates the FCEV's performance in providing power to the grid, with a Tank-To-AC-Grid efficiency of 44%. Two operating modes for the FCEV in a residential microgrid are identified: fixed power output and load following. Batteries like lithium ion [24] play a critical role in electric vehicles, serving as the primary energy storage system that powers the vehicle and determines its range, performance, and efficiency [25]. Electric vehicles have some challenges; low phase noise class-C oscillator can enhance signal stability and efficiency in electric vehicle communication and control systems [26]. This improved class-C oscillator can enhance signal reliability and energy efficiency in electric vehicle communication systems [27]. The studies [28]-[30] contribute to electric vehicle advancements through optimized supply chains, scalable data forwarding, and improved lithium-sulfur battery performance.

In Orebro, Sweden, a PV system design for residential and EV charging demand is proposed by Khan et al [31]. It assesses how various PV systems and roof slopes perform in terms of technology, economy, and the environment. A roof angle of 45° has the shortest payback period, and bifacial photovoltaic systems perform better in terms of energy generation. Certain economic statistics apply to the monofacial photovoltaic system with a 30° slant. Because of Sweden's low grid emission factor, EVs have a greater impact on reducing GHG. This research offers guidance on how to satisfy location-specific energy needs. Chai et al. developed a two-stage optimization technique for the Vehicle-to-Grid (V2G) scheme, considering the perspectives of both building owners and EV owners [32]. The technique focuses on the travel convenience of EV owners by providing two V2G options. The first stage involves day-ahead optimization (DAO) to minimize the building's maximum demand. The second stage involves real-time optimization (RTO) to adjust the V2G operation based on actual vehicle behaviors. Simulations show that the proposed technique can adjust EV charging or discharging in real-time. A cost-benefit analysis is also conducted to assess the savings and rewards for both the building and EV owners.

Zhang et al. used a multivariate load prediction model for buildings integrated with EVs considering occupant travel [33]. The model incorporates different methods to obtain travel variables and constructs an occupant travel behavior model using Monte Carlo simulation. Data-driven approaches such as artificial neural networks, LSTM, and TPA-LSTM are used to build the load prediction model. The results show good synchronization between building load and EV charging load, with the TPA-LSTM model achieving high prediction accuracy. This study provides an effective tool for accurate load prediction in EV-integrated buildings. Mansouri et al. [34] presented a nest framework to address flexibility challenges in renewable-based transmission and distribution systems. The framework utilizes distributed energy resources (DERs), smart buildings, and electric vehicle fleets to provide flexibility. A novel demand response program (DRP) is designed with time-varying tariffs based on flexibility requirements. The coordination between the transmission system operator (TSO) and distribution system operator (DSO) is formulated as a computationally tractable problem. Battery energy storage systems (BESSs) manage extreme conditions. Simulation results demonstrate improved economic, technical, and security aspects of TSO-DSO coordination. The work of reference [35] introduces an advanced Smart Energy Management System (SEMS) featuring a one-hour resolution for optimizing energy use in nearly-zero energy buildings (NZEB) through Vehicle-to-Building (V2B) technology. The system reduces grid reliance by 65% and carbon emissions by 64%, integrating EV charging/discharging schedules with renewable energy resources and battery storage. It also incorporates real-world EV parking patterns and considers battery degradation costs in its economic analysis. The study highlights the cost-effectiveness and sustainability of combining photovoltaic (PV) systems with V2B, contributing to the development of net-zero cities.

Reference [13] examines the integration of plug-in electric vehicles (PEVs) with energy-flexible buildings, focusing on the challenges of PEV charging on building power demand and co-management strategies for optimized energy use. It highlights the role of microgrid technology in combining distributed energy sources, storage, and diverse consumers to accommodate growing PEV charging demands while minimizing impacts on power demand profiles and distribution transformers. The paper provides a comprehensive review of current research on co-management technologies and identifies key factors and co-benefits of integrated energy systems. It also addresses the need for improved control methods to support the increasing penetration of PEVs in buildings. The work in of reference [36] explores how PEVs can contribute to the self-sustainability of nearly zero-energy buildings (ZEBs) by supplying part of their battery capacity to residential appliances. The study focuses on minimizing energy exchange with the external grid while considering the limited cooperation of PEV owners due to their need to maintain a preset driving range. It also examines the role of fixed battery systems in compensating for the variability in PEV owners' cooperation. Ref. [37] presents two electric energy management systems (EMSs) designed for a grid-connected residential neighborhood with EVs, battery storage, and solar photovoltaic (PV) generation. The EMSs aims to minimize electricity costs without affecting residents' energy needs or travel patterns. The study compares centralized and decentralized EMSs, accounting for battery capacity degradation and its costs, using real data from a high-density residential building in Sydney, Australia. Simulation results show that the centralized EMS outperforms the decentralized EMS in cost savings and significantly reduces reliance on grid energy compared to unoptimized strategies.

Integrating EV charging stations into buildings significantly reduces greenhouse gas emissions by promoting the use of electric vehicles over traditional gasoline-powered vehicles. EVs produce zero tailpipe emissions, thereby decreasing the overall carbon footprint. When combined with renewable energy sources, the emissions reduction can be even more substantial.

The shift from internal combustion engine vehicles to electric vehicles helps improve air quality, especially in urban areas. EVs do not emit pollutants such as nitrogen oxides and particulate matter, which are major contributors to air pollution and respiratory diseases. This transition contributes to cleaner air and better public health outcomes. Integrating EV charging stations with smart building energy management systems can optimize energy use and improve overall energy efficiency. By using renewable energy sources like solar or wind power, buildings can reduce their reliance on fossil fuels, further lowering their environmental impact. Buildings equipped with EV charging stations can take advantage of distributed energy resources (DERs), such as solar panels and energy storage systems. This integration allows for more efficient use of renewable energy, reducing the need for grid electricity and minimizing energy losses. Additionally, EVs can act as mobile energy storage units, providing backup power to buildings during peak demand or emergencies. Promoting the use of EVs reduces dependency on fossil fuels, thereby conserving finite natural resources. This shift supports the transition to a sustainable and resilient energy system, decreasing the environmental degradation associated with fossil fuel extraction [38], [39].

Electric vehicles are quieter than their internal combustion engine counterparts, leading to reduced noise pollution, especially in densely populated urban areas. This improvement in noise levels enhances the overall quality of life for residents. Integrating EV charging stations into buildings aligns with green building standards and certifications, such as LEED (Leadership in Energy and Environmental Design). These standards encourage the adoption of sustainable practices, resulting in more environmentally friendly and energy-efficient buildings. By providing convenient access to EV charging stations, buildings can encourage the adoption of electric vehicles and sustainable transportation habits. This shift can reduce traffic congestion, lower emissions, and promote a healthier environment. The widespread integration of EV charging stations can influence urban planning and development strategies. Cities can design infrastructure that supports sustainable transportation, reduces urban sprawl, and promotes the development of walkable, transit-friendly communities. Investing in EV charging infrastructure can create economic opportunities and environmental benefits simultaneously. Job creation in the green technology sector, reduced healthcare costs due to improved air quality, and enhanced energy security are just a few examples of the positive synergies that can be achieved.

Effective stakeholder engagement is crucial for successfully integrating EV charging stations into buildings. Government and regulatory bodies set supportive policies and incentives, ensuring compliance. Building owners and property managers oversee installation and maintenance, while utility companies provide necessary electrical infrastructure and manage grid stability. EV manufacturers and charging equipment providers supply and support high-quality technology. Environmental organizations advocate for sustainable transportation, and local communities and EV owners offer feedback and participation in pilot programs. Financial institutions and investors provide funding and evaluate economic viability, and technology providers develop smart energy management systems to enhance user experience. By collaborating effectively, these stakeholders ensure the efficient and sustainable integration of EV charging stations. Government incentives and supportive policies create a favorable environment, while utility companies manage energy distribution and grid performance. Building owners and property managers ensure safety and compliance, and EV manufacturers provide reliable technology. Environmental organizations and local communities promote adoption and accessibility, and financial institutions fund the infrastructure. Technology providers optimize integration, ensuring the infrastructure meets the needs of all users. This collective effort balances costs, efficiency, and sustainability, contributing to the broader goal of reducing greenhouse gas emissions and promoting clean energy solutions.

The COVID-19 pandemic significantly disrupted the adoption of electric vehicles and the development of related infrastructure due to economic slowdowns and supply chain interruptions. Despite these challenges, EV sales continued to grow in regions with strong governmental support, such as China and Europe. These areas saw increased investments in EV infrastructure, with policies and incentives encouraging EV adoption even amidst the pandemic. However, in other regions, market recovery was slower, and consumer purchasing power was affected, potentially delaying broader adoption. Consumer behavior shifted as economic uncertainties and reduced oil prices made cost-conscious decisions more prevalent. Although EVs generally offer lower total ownership costs, the narrowed cost advantage due to falling gasoline prices influenced purchasing decisions in some markets. The pandemic also highlighted the need for enhanced energy management strategies and flexible infrastructure to accommodate fluctuations in demand and supply chains. Governments and private sectors responded with various policies, subsidies, and investments to mitigate these disruptions and support the transition to EVs. Long-term, the pandemic underscored the importance of sustainable transportation solutions and the resilience of the EV market. It prompted a reevaluation of urban planning and energy management to better integrate EV infrastructure with renewable energy sources. Future research should focus on understanding the long-term impacts of COVID-19 on EV adoption, examining how policy adjustments and technological advancements can continue to support the growth of EV infrastructure and the broader shift towards clean energy solutions. Integrating smart technologies into EV charging stations can greatly enhance efficiency, reliability, and user experience. Smart energy management systems use real-time data and advanced algorithms to optimize energy consumption, balancing demand and reducing peak loads. The Internet of Things (IoT) connects devices for seamless communication, enabling real-time monitoring, predictive maintenance, and remote troubleshooting, ensuring the infrastructure remains efficient. Also, machine learning has several applications [40].

Smart grid integration allows buildings to participate in demand response programs, adjusting charging loads based on grid conditions to stabilize the grid and reduce costs. User-friendly applications provide real-time information on charging status and availability, enhancing convenience. Additionally, artificial intelligence can predict energy demand and optimize charging schedules, while renewable energy integration maximizes the use of clean energy for charging [41]. By incorporating these technologies, EV charging infrastructure can be more sustainable and efficient, supporting broader environmental goals and improving overall energy management. This cohesive approach enhances the relevance and effectiveness of the charging system, ensuring it meets the needs of all stakeholders.

2. METHODS

The integration of EV charging stations into buildings requires a comprehensive system modeling approach to balance energy consumption, cost efficiency, and environmental impact. To achieve this, the study employs a multi-objective optimization framework that considers various operational and environmental variables. Key components of the model include energy demand profiles, building occupancy patterns, meteorological data, and EV charging habits. Energy demand profiles are modeled using historical and predictive data, enabling the system to adapt to fluctuations in usage. Building occupancy patterns, which significantly influence energy consumption, are analyzed through dynamic scheduling and simulation techniques. Additionally, meteorological data is integrated into the model to account for the effects of weather conditions on both building energy needs and renewable energy generation.

The model also incorporates detailed simulations of EV charging habits, including charging frequency, duration, and energy requirements. By analyzing real-world data and predicting trends, the model can capture the variability in EV energy demand. The interaction between building energy systems and EV stations is represented through Mixed Integer Linear Programming (MILP), which allows for the inclusion of both discrete and continuous variables. This modeling approach facilitates the evaluation of different operational scenarios and trade-offs, ensuring that the system remains flexible and reliable under varying conditions. The integration process also considers uncertainties, such as changes in user behavior or grid availability, by implementing robust optimization techniques. Through this detailed and adaptive modeling, the system is designed to achieve optimal performance in terms of cost, energy efficiency, and sustainability. Multiple competing objective functions are present in multi-objective MILP issues. This implies that no single ideal solution is able to fulfil every requirement at the same time. Alternatively, there are several Pareto-optimal alternatives. In terms of objective values, these are the only possible alternatives that do not dominate any other answer [42]. A Pareto operation is the process of identifying and evaluating these Pareto optimal solutions for a particular multi-objective MILP problem. Pareto operations can be carried out in a variety of ways, each with unique benefits and drawbacks. The situation and the needs of the decision-maker determine which approach is best [43].

1. Multiple-weighted sums method: The multiple-weighted sums approach combines all of the objective functions into a single objective function by giving each one a weight. Different Pareto optimum solutions can be achieved by adjusting the weights. However, this approach might not be able to produce the whole Pareto front, particularly in the case of non-convex or discontinuous situations [44].

   In the Multiple-weighted sums method, the multi-objective problem is transformed into a single-objective problem by assigning a weight to each objective function and then aggregating them into a single objective function. The mathematical formulation of this method can be represented as follows:
   Given a multi-objective MILP problem with n objective functions $f1$, $f2$, ..., fn, and a set of weights $w1$, $w2$, ..., wn, the single-objective function F can be calculated as (1).

$$F(x) = \sum_{i=1}^{m} \omega_i * f_i(x) \tag{1}$$

   By varying the weights $w1$, $w2$, ..., wn, different Pareto optimal solutions can be obtained. Each solution represents a different trade-off between the objectives. The weights can be adjusted to reflect the decision-maker's preferences, allowing for a customized analysis that considers the specific priorities and constraints of the problem at hand. However, it's important to note that this method may not be able to generate the entire Pareto front, especially for non-convex or discontinuous problems.

2. Epsilon-constrained method: This technique fixes the values of all but one objective function inside a set of boundaries (epsilon), converting the multi-objective MILP issue into a sequence of single-objective MILP problems. Every single-objective MILP problem can have a Pareto optimum solution by solving it. One can find alternative Pareto optimum solutions by varying the epsilon values. The full Pareto front can be generated by this method, although it might need a lot of epsilon values to accomplish.

   Given objective functions $f_1(x)$, $f_2(x)\ldots f_m(x)$ to be optimized, and constraint functions $g_j(x) \leq 0$, j=1,2,...,p derived from the remaining objectives, the epsilon-constrained problem can be formulated as:
   Minimize:
   $f_1(x)$
   Subject to: (2)

$$f_i(x) \leq \epsilon i, \text{ for } i=2,3...,m$$

$$g_j(x) \leq 0, \text{ for } j=1, 2...,p \tag{3}$$

   In (2), the primary objective $f_1(x)$ is optimized while the other objectives are treated as constraints with epsilon bounds. By adjusting the epsilon values, a set of Pareto-optimal solutions can be identified. This method helps in exploring the trade-offs between different objectives in multi-objective optimization problems.

3. Multiple single-objective Pareto sampling: By sampling the objective space and resolving a single-objective MILP problem at every sample point, this technique yields a set of Pareto optimal solutions. In order to fully cover the Pareto front, the sample points were selected. This algorithm may not be able to produce all of the Pareto optimal

solutions, but it can handle many objectives and determine the boundaries and discontinuities of the Pareto front [45].

The formulation for this approach can be represented as follows:

Given:

- Objective functions: $f_1(x), f_2(x)..., f_m(x)$
- Decision variables: $x = (x_1, x_2,...,x_n)$
- Constraints: $g_i(x) \leq 0, i=1,2...,p$

The MILP problem at each sample point can be formulated as:

Minimize:

fj(x)

Subject to:

$$f_i(x) \leq \epsilon i, \text{ for } i \neq j \tag{4}$$

$$g_i(x) \leq 0, \text{ for } i=1,2...,p \tag{5}$$

Here, *j* represents the objective function being optimized at that sample point, while the other objective functions are treated as constraints with epsilon bounds. By solving this MILP problem at multiple sample points across the objective space, a diverse set of Pareto optimal solutions can be obtained, contributing to a better understanding of the Pareto front's shape and characteristics.

4. Pareto-based multi-objective machine learning: This approach approximates the Pareto front and the goal functions of a multi-objective MILP issue using machine learning techniques. The Pareto optimal solutions acquired through alternative methods are employed to train the machine learning models. Subsequently, the objective values and Pareto optimality of novel solutions can be predicted by the trained models. This method may result in some inaccuracies and uncertainties in the outcomes, but it can also save the computational cost and time needed to answer a multi-objective MILP problem.

The formulation for this approach involves using machine learning models to predict the objective values and Pareto optimality of solutions. Here is a general representation:

Given:

- Objective functions: $f_1(x), f_2(x)..., f_m(x)$
- Decision variables: $x = (x_1, x_2..., x_n)$

The machine learning model is trained using Pareto optimal solutions x^* and their corresponding objective values $f(x^*)$ acquired from alternative methods.

The trained machine learning model can then predict the objective values $f(x)$ and Pareto optimality of a new solution xx. The formulation can be represented as follows (6).

Predict:

$$\hat{f}(x) = ML\ (x^*, f(x^*), x) \tag{6}$$

In (6), $\hat{f}(x)$ is the predicted objective values for the new solution xx, *ML* represents the trained machine learning model using the Pareto optimal solutions x^* and their objective values $f(x^*)$ as training data.

By utilizing machine learning techniques in this manner, the Pareto-based multi-objective machine learning approach aims to provide efficient predictions of objective values and Pareto optimality for new solutions in multi-objective MILP problems.

Using the Multiple-Weighted Sums approach, the Pareto operation for the trade-off analysis between the building and the charging station is carried out in this work. Because it enables a thorough examination of the trade-offs between various objectives, this approach is especially helpful in scenarios where there are several competing goals [46]. By giving each objective function a weight and then combining them into a single objective function, the multiple-weighted sums approach operates. Different Pareto optimum solutions can be achieved The Multiple-weighted sums approach transforms the multi-objective problem into a single-objective problem by assigning a weight to each objective function and then aggregating them into a single objective function. By adjusting the weights, different Pareto optimal solutions can be achieved, which represent different trade-offs between objectives. This method is particularly useful in scenarios with multiple competing goals.

The research considers several items, such as fluctuations in energy use and EV charging habits, to create a reliable and flexible integration system. By modeling variables like occupancy levels, meteorological conditions, and usage patterns, the integration process aims to optimize energy usage, maximize cost savings, and reduce environmental impact. Collaborative strategies are also emphasized for their superiority in achieving cost savings compared to non-cooperative alternatives. By adjusting the weights, this offers a variety of options, each of which represents a unique trade-off between the goals. The Multiple-weighted sums method's simplicity and convenience of use are among its key benefits. It is easy to apply to a variety of issues since it doesn't require any complicated transformations or extra constraints. Its adaptability is an additional benefit. The decision-makers preferences can be reflected in the weights, enabling a tailored analysis that considers the priorities and restrictions of the given problem [47].

In order to create a reliable and flexible integration system, our research considers many uncertainties, including fluctuations in energy use and EV charging habits. To gain a deeper understanding of the energy demand profile, we will investigate variables such as shifting occupancy levels, meteorological conditions, and usage patterns. To further improve the integration process, we will model the charging habits and durations of EVs. Our goals are to reduce the environmental impact of the vehicle-to-building integration, maximize cost savings, and optimize energy usage by including these uncertainties into our study. Since collaborative strategies have been shown to outperform non-cooperative alternatives in terms of cost savings, they will be crucial to accomplishing these goals. To advance vehicle-to-building systems, we can leverage insights and methodologies from a wide array of research articles and studies. These scholarly works provide valuable strategies to address the inherent uncertainties and challenges in V2B integration. By analyzing existing literature, we can refine energy forecasting models, improve collaborative control mechanisms, and enhance algorithms for optimizing energy distribution between vehicles and buildings [48]-[52]. Moreover, incorporating diverse approaches discussed in research such as demand-response strategies, advanced energy storage systems, and renewable energy integration can significantly elevate the reliability and sustainability of V2B systems. These findings not only support environmental goals but also contribute to creating scalable, adaptive solutions for a variety of scenarios. Collaborative research plays a pivotal role in shaping robust and innovative V2B integration frameworks [53]- [57].

3. DATA PREPROCESSING

a. Data Collection: Gathering data on building energy consumption, EV charging habits, weather conditions, occupancy levels, and cost information.
b. Data Cleaning: Handling missing values, removing duplicates, and detecting outliers to ensure high data quality.
c. Data Transformation: Normalizing energy data, encoding categorical variables, and engineering features to enhance analysis.
d. Data Integration: Merging datasets and joining tables to create a comprehensive dataset.
e. Data Reduction: Applying dimensionality reduction techniques and sampling to streamline the dataset.
f. Data Validation: Conducting validation checks and cross-validation to ensure data integrity.
g. Data Analysis: Utilizing Pareto frontier analysis and Multi-Objective Optimization (MOO) to identify optimal trade-offs among objectives, with Strategy C emerging as the most balanced and cost-effective solution.

4. RESULTS AND DISCUSSIONS

In this section, we delve into the simulation results of the proposed cooperative decision-making model for vehicle-to-building integration. The decision-making process is intricately divided into hourly segments that span the entirety of a day. Our model leverages hourly data concerning the thermal and electrical energy consumption of a mid-sized office building in Chicago on a summer day. Furthermore, the cost of energy from a nearby electrical source is meticulously factored in when scrutinizing operational choices. To ascertain the quantity and availability of electric vehicles (EVs), we tap into insights derived from the driving behaviors and geographical locations of EV owners. The battery management system offers crucial details on the initial and planned states of charge (SOC) of the EVs, which stand at 27% and 58%, respectively catering aptly to daily driving requirements.

The concept of the Pareto frontier emerges as a formidable tool in economics and decision-making realms. It delineates the optimal solutions set for a given predicament, where enhancing one solution inevitably leads to the degradation of another. This concept proves particularly invaluable in scenarios necessitating trade-offs between diverse objectives or criteria. Consider the scenario of electric vehicle charging stations. Here, the overarching goal might encompass reducing operational costs for both the building and the charging station while concurrently maximizing service quality and customer satisfaction. The Pareto frontier emerges as a guiding beacon, aiding in identifying the optimal blend of these facets, considering the available resources and constraints. Visualizing the Pareto frontier is adeptly achieved through a scatter plot graph. Each plotted point symbolizes a potential solution, with the axes denoting varying objectives or criteria. For instance, within the domain of electric vehicle charging stations, the x-axis could epitomize the building operation cost, while the y-axis could mirror the charging station operation cost. The plotted points lay bare the diverse cost combinations across myriad scenarios or locales. The Pareto frontier, depicted by the green line linking select points, delineates the optimal solutions unalterable without augmenting one of the costs. Points beneath or left of the Pareto frontier are overshadowed by the frontier points, indicating escalated costs for both the building and the charging station. Conversely, points above or to the right of the frontier are deemed unattainable, indicative of their impracticability within the existing resource framework.

Decision-makers are steered by the Pareto frontier towards selecting the optimal solution for their quandary, contingent on their preferences and priorities. For instance, if the aim is to curtail the overall operational costs of both the building and the charging station, the decision-maker might opt for the point on the Pareto frontier showcasing the lowest sum of the x and y values. Should the goal be to strike a balance between the building and charging station costs, selecting the point with the minimal disparity between the x and y values on the frontier is prudent. In the realm of electric vehicle charging stations, particularly in rural locales with fluctuating electricity demand-supply dynamics, the Pareto frontier emerges as a potent tool for assessing cost-effectiveness. By leveraging the Pareto frontier, one can juxtapose diverse scenarios or locales, pinpointing the optimal equilibrium between the expenses and advantages of establishing and operating charging stations. The Pareto frontier additionally facilitates evaluating the repercussions of diverse policies or incentives on the cost-effectiveness of charging stations, encompassing subsidies, taxes, tariffs, or regulations. This renders the Pareto frontier an indispensable asset in decision-making and resource allocation, empowering stakeholders to make informed and strategic choices in complex and multifaceted environments.

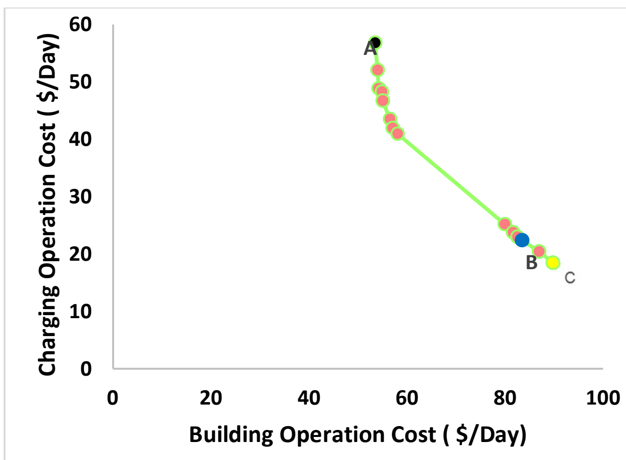

Figure 1. Pareto Frontier Analysis of Building and Charging Station Integration Operational Costs.

Applying Pareto optimal solutions to the Multi-Objective Optimization (MOO) problem yields truly remarkable outcomes. This approach is renowned for its straightforward implementation and exceptional efficacy, especially when tackling objectives with fewer quantities. The weighted sum approach emerges as a valuable instrument for delineating the priorities of both the building and the charging station within the broader energy system landscape. Notably, an incremental adjustment of 0.031 is employed for updating the weights, ensuring a nuanced calibration of priorities.

The graphical representation of the Pareto frontier in Figure 1 illustrates the dynamic pricing scheme's impact on the operating costs of the building and the charging station. Each point along this frontier, stemming from the non-dominated energy dispatch method, encapsulates the intricate equilibrium between the building and the charging station as they vie for energy allotment. Within the realm of the Pareto frontier, distinct points convey nuanced scenarios. Point A ($53.99, $52.0688) signifies the scenario where the building secures the most cost-effective solution. In contrast, Point C ($89.75, $18.476) epitomizes the Pareto solution, indicating the charging station's optimal cost efficiency. Noteworthy is Point B ($86.87, $20.45), representing the nexus of minimum total cost a pivotal position that impeccably balances the operational expenses of the building and the charging station. This juncture encapsulates the optimal equilibrium sought between the two entities.

Figure 2 illustrates the Pareto Frontier Analysis from Buildings to Charging Stations Station Electricity Transmission under Operation Strategies A, B, and C. Strategy A is the most conservative one, as it does not transmit any electricity from the building to the charging station until the last 8 hours of the day. This means that the building is saving electricity for its own use or for selling it to the grid at a higher price. However, this also means that the charging station is not getting any benefit from the building's surplus electricity and may have to rely on other sources of power. Strategy B is the most aggressive one, as it transmits the maximum amount of electricity from the building to the charging station for the first 16 hours of the day. This means that the building is sacrificing its own electricity consumption or profit to support the charging station. This could be beneficial for the charging station if the demand for charging is high and the price of electricity is low. However, this also means that the building is risking running out of electricity or having to buy it from the grid at a higher price. Strategy C is the most balanced one, as it transmits a moderate amount of electricity from the building to the charging station throughout the day. This means that the building is adjusting its electricity transmission based on the demand and price of electricity. This could be optimal regarding the building and the charging station, as they can share the benefits and risks of the electricity market.

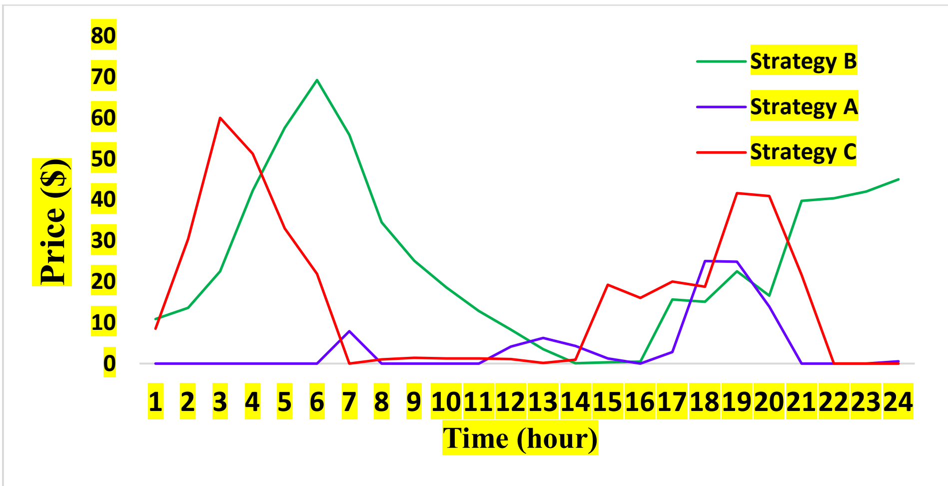

Figure 2. Pareto Frontier Analysis of Electricity Transmission from Buildings to Charging Stations under Operation Strategies A, B, and C.

Figure 3 compares the three strategies in terms of electricity transmission from the charging station to the building. Strategy A: In this strategy, the building does not rely on charging stations for electricity supply throughout the entire 24-hour period. This implies that the building has an alternative source of power and does not require electricity from the charging station during this time. There is no transmission of electricity from the charging station to the building. Strategy B: This strategy involves occasional transmission of a small amount of electricity from the charging station to the building. The amount of electricity transmitted ranges from 0.0177438 KW to 0.679161 KW. Although this amount is minimal, it indicates that the charging station can provide a minor contribution to the building's power supply in certain instances. However, it is not a significant or consistent source of electricity for the building. Strategy C: Like Strategy A, no electricity is transmitted from the charging station to the building in Strategy C. The building does not receive any power from the charging station in this scenario. Overall, Strategies A, B, and C do not involve substantial electricity transmission from the charging station to the building. These strategies primarily focus on the flow of electricity from the building to the charging station, suggesting that the building may be the primary source of power for the charging station. However, without additional context or information, it is difficult to draw definitive conclusions about the rationale behind these strategies or their effectiveness.

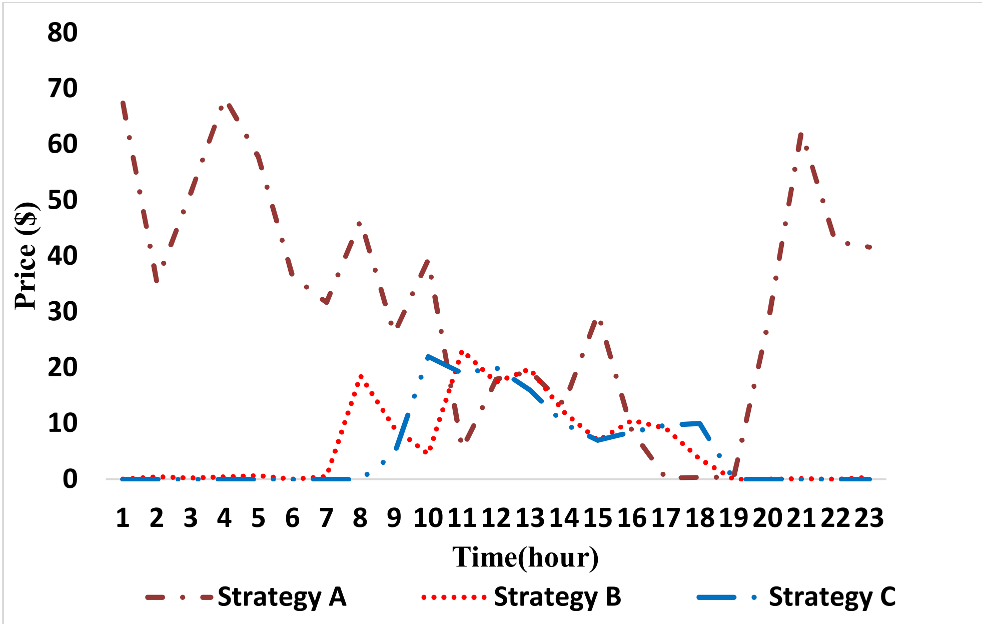

Figure 3. Pareto frontier analysis from Charging Stations station to Buildings electricity transmission for Operation Strategies A, B, and C.

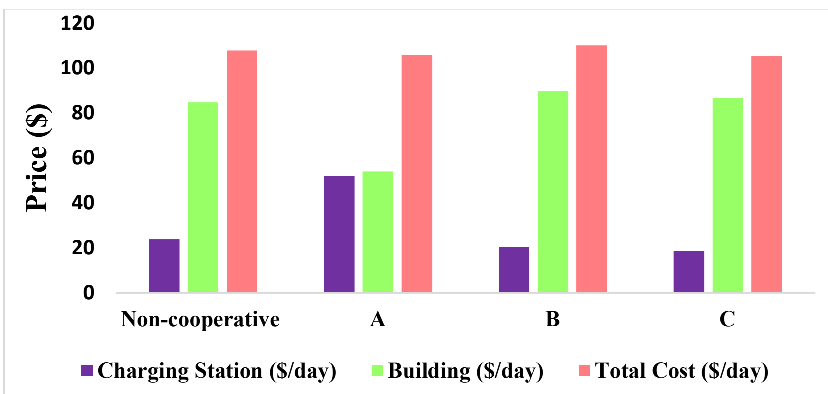

Figure 4. Comparing Operational Strategies: Collaborative and non-cooperative.

In Figure 4, a detailed cost analysis unveils insights into four distinct scenarios entwining the charging station and the building. In the non-cooperative scenario, the charging station accrues a daily cost of $23.87, juxtaposed with the building's expense of $84.9 per day. The cumulative cost in this scenario tallies up to $107.9 daily. Transitioning to the three strategic frameworks, Strategy A unfolds with a charging station cost of $52.0688 per day and a building cost of $53.99 daily. Consequently, the total cost for Strategy A stands at $106.0588 per day. Strategy B delineates a charging station expenditure of $20.45 per day, accompanied by a building cost of $89.75 per day, culminating in a total outlay of $110.2 daily. Strategy C, in contrast, manifests a charging station cost of $18.476 per day and a building cost of $86.87 daily, resulting in a total cost of $105.346 per day.

Upon scrutinizing the figure, a discernible pattern emerges. Strategy C emerges as the pinnacle of cost-effectiveness among the three strategies, offering the most economical solution at $105.346 per day. Strategy A clinches the runner-up position with a marginally higher total cost of $106.0588 per day. Conversely, Strategy B grapples with the highest total cost among the strategies, peaking at $110.2 per day. While cost stands paramount in the decision-making process, it is imperative to acknowledge that additional facets such as efficiency, reliability, and the tailored requisites of both the charging station and the building necessitate consideration. A comprehensive assessment, amalgamating these supplementary factors with cost considerations, is imperative to ascertain the most fitting strategy.

5. CONCLUSION

This study demonstrates significant advancements in the integration of electric vehicle (EV) charging stations within buildings, contributing to sustainable energy management and greenhouse gas reduction. By employing Pareto frontier analysis and Multi-Objective Optimization (MOO) methods, the research successfully identifies Strategy C as the most balanced and cost-effective approach for vehicle-to-building energy integration, minimizing operational costs while ensuring system efficiency and reliability. The study provides a systematic framework for decision-makers to navigate the complexities of energy management, incorporating environmental, economic, and operational considerations, which enables informed decisions aligned with broader sustainability goals. Moreover, the findings emphasize the importance of prioritizing cost-effectiveness and system efficiency in the integration process, equipping stakeholders with actionable insights to optimize energy usage and enhance building functionality. The integration of EV charging stations not only supports the widespread adoption of electric vehicles but also aligns with global sustainability initiatives, advocating for innovative solutions that contribute to a cleaner environment. Finally, the methodologies and strategies proposed lay a robust foundation for further advancements in energy-efficient systems, opening avenues for exploring additional technological innovations, such as smart grid solutions and renewable energy integration. In summary, this research not only advances the understanding of integrating EV charging stations in buildings but also provides practical pathways for stakeholders to achieve net-zero energy objectives, highlighting the critical role that buildings can play in fostering a sustainable future and driving progress toward widespread EV adoption and improved energy management practices. Building on the findings of this study, several areas warrant further investigation to enhance the integration of EV charging stations into buildings. Future research should explore how different seasons, building types, and geographical locations affect energy consumption patterns and EV charging behaviors. Additionally, investigating the long-term performance and scalability of integrated EV charging infrastructure is essential, considering evolving technologies, market conditions, and regulatory environments. Advanced energy management systems, utilizing machine learning algorithms and predictive analytics, can further optimize interactions between building energy use, EV charging, and renewable energy sources. Furthermore, understanding user behavior and acceptance of EV charging infrastructure is key to successful implementation. Detailed analyses of the economic and environmental trade-offs involved, as well as the impact of various policies, incentives, and regulations, are crucial. Research should also explore the integration of EV charging stations with smart grids and IoT for enhanced grid stability and real-time data monitoring. Addressing these areas will build on the current study's findings and contribute to more effective, sustainable, and user-friendly EV charging infrastructure.

DECLARATIONS

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